

# NAVAL POSTGRADUATE SCHOOL

**MONTEREY, CALIFORNIA** 

# **THESIS**

# A TIME SERIES ANALYSIS OF U.S. ARMY OFFICER LOSS RATES

by

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June 2005

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Captains and majors comprise a critical management population in the United States Army's officer corps. This thesis analyzes U.S. Army officer loss rates for captains and majors and evaluates the fit of several time series models. The results from this thesis validate the time series forecasting technique currently used by the Army G-1, Winters-method additive.

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# A TIME SERIES ANALYSIS OF U.S. ARMY OFFICER LOSS RATES

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Submitted in partial fulfillment of the requirements for the degree of

## MASTER OF SCIENCE IN OPERATIONS RESEARCH

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Captains and majors comprise a critical management population in the United States Army's officer corps. This thesis analyzes U.S. Army officer loss rates for captains and majors and evaluates the fit of several time series models. The results from this thesis validate the time series forecasting technique currently used by the Army G-1, Winters-method additive.

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#### **EXECUTIVE SUMMARY**

Accurate prediction of officer loss behavior is essential for the planning of personnel policies and executing the U.S. Army's Officer Personnel Management System (OPMS). Inaccurate predictions of officer strength affect the number of personnel authorizations, the Army's budget, and the necessary number of accessions. Imbalances of officer strength in the basic branches degrade the Army's combat readiness as a whole. The objective of this thesis is to conduct a time series analysis of U.S. Army officer loss rates for captains and majors and identify a time series model that accurately predicts the expected number of commissioned officer losses for each basic branch by grade (captain and major).

Individual loss and gain records from October 1998 thru September 2004, obtained from the Total Army Personnel Database-Active Officer (TAPD-AO), were aggregated by grade and basic branch. The aggregated data form a time-series of net losses. Time-series for each grade (O-3 and O-4) and basic branch were analyzed using SAS Time-Series Forecasting System (TSFS).

Ten time-series models, determined to be appropriate for the data, were fit to the data using SAS TSFS. Akaike's Information Criterion was used to evaluate the fit of each of the ten models. Two models, seasonal exponential smoothing and Winters method-additive, distinguished themselves from the others. These two models had the best fits in every series.

Winters method-additive, the current forecasting technique used by the Strength Analysis and Forecasting Branch, Army G-1, is validated. Although seasonal exponential smoothing is less complex, having one less parameter, the increase in fit as measured by AIC is negligible.

However, these best fitting models have weak predicting power. Predictions from the seasonal exponential smoothing model for 2004 were compared to the corresponding observed values in our test set. The observed and predicted values for captains have a correlation of .21; for majors the correlation is .52.

A comparison of the results of multiple regression and time-series is worth investigating. Such a study would require the collection of external monthly econometric variables such as gross domestic product, unemployment rate, durable good orders, and so on. Multiple regression may achieve better fitting models than the time-series shown here.

## I. INTRODUCTION

#### A. BACKGROUND

The Army is currently transforming its structure and moving toward a modular force. The Army Chief of Staff, General Peter Schoomaker, stated this very clearly in a July 2004 Defense Department Special Briefing on U.S. Army transformation when he said:

We are changing our Army along three primary avenues — and this is important, I believe, as we talk about this the rest of the afternoon, the time that we have together, to think in terms of the context of what we're doing. The first is that we are restructuring the force into modular formations. And we're calling these the combat forces, brigade combat team[s], units of action. And this [is] a path on the transformation towards the eventual Future Combat System — units of action. (Defense Department, 2004)

In conjunction with this structure change, the Deputy Chief of Staff, Army G-1 is currently involved in changing the way officers are managed in the promotion and career field designation (CFD) process. These changes require a forward-looking ability in order to predict what each branch or career field will look like in the future.

The Army is redesigning the Officer Personnel Management System (OPMS). In past years the Army has conducted a functional area (FA) designation between the 5<sup>th</sup> and 6<sup>th</sup> year of an officer's service. This timing was logical. It allowed an officer to complete a company command in his or her basic branch prior to FA designation and then alternate between basic branch and FA assignments thereafter. In the past, all officers received their FA designation from a preference-based board. However, the reality was that very few actually served in a FA position as a captain. At the time of this writing (April, 2005), CFD occurs at the ten-year time in service point. An officer retains and will work in this career field for the duration of his or her career. The result is often officers whose FA designations do not align with their CFD and hence do not support Army requirements.

As a result, Officer Personnel Management Division (OPMD) directed that starting with Cohort Year Group 1999, officers no longer go before a FA designation

board or be designated a second career field (U.S. Army Officer Professional, 2004). FA proponents now review the entire year group and are able to identify, recruit, and select officers to serve a FA assignment.

The current system designates an officer into a career field after selection to major, which occurs at about the 10-year point. After career field designation the officer remains in that branch or career field full-time. Since many career fields invest a lot of time (up to three years of training) and money in qualifying officers, the Army is moving toward early designation of a limited number of officers starting at the seven-year mark. To decide which branches these early career-field designated officers will come from and to which branches they will go, the Army must be able to accurately predict the number of officers expected to be in each branch at the ten-year point.

For promotion and career field designation purposes, the Career Systems Analysis and Studies Branch looks at the strength of the entire rank into which the board will promote officers. The predicted number of promotions from the primary zone, above the zone and below the zone is added to the current strength to determine post-board strength for each branch or career field. This expected strength is then compared to the force structure requirements of the promotable rank to determine the number of promotions or career field designations needed for each branch or career field.

Inaccurate predictions of officer strength affect the number of personnel authorizations, the Army's budget, and the necessary number of accessions and losses. Imbalances of branches and career fields affect the Army's combat readiness as a whole. The results from this thesis will help the Army G-1 to assess current force structure and readiness, determine loss and accession policies, and contribute to the design of the future force structure of the Army.

#### B. THESIS OBJECTIVE

#### 1. Objective

Captains and majors comprise a critical management population. In this thesis we conduct a time series analysis of U.S. Army officer loss rates for captains and majors and identify a time series model that accurately predicts the expected number of

commissioned officer net losses for each basic branch by grade (O-3 and O-4). The following tasks were performed pursuant to this objective:

- a. Monthly historical data containing individual loss, gain, and promotion records was constructed from queries into the Total Army Personnel Data Base-Active Officer (TAPDB-AO). The first five years of data was used as training data to identify the best models. The last year of data was used as test data. The test data was quarantined and used later to evaluate the best model.
- b. The current forecasting technique, Winters Additive, was included to establish a baseline for comparison of the other techniques considered and to gain insight into the techniques' accuracy.
  - c. Other models were developed.
- d. Measures of accuracy were developed and used to evaluate each predictive technique.
- e. A comparative analysis of each forecasting technique was conducted to identify the model that provided the most accuracy.
- f. Forecasts from the best model were compared against observed values in the test set to evaluate the models predictive power.

## 2. Organization

This introductory chapter provides the reader with a description of the problem and the organization of the thesis. It also provides the motivation for conducting this research.

Chapter II contains a description of the TAPDB-AO data provided by the Army G-1, Deputy Chief of Staff, Career Systems Analysis and Studies Branch. It also describes problems with the data and how these problems were resolved.

Chapter III contains the details of how the analysis was conducted. It first describes how the data was sorted for analysis. Secondly, it describes each time series model considered in the analysis that was used to forecast expected loss rates. Finally, the chapter describes the goodness of fit measures used to compare the models.

Chapter IV contains the analysis of results. The best fitting models, for each basic branch and grade (O-3 and O-4), are presented in table form. The best fitting models are evaluated by comparing their predicted values against observed values in our test set. This chapter concludes with a summary of results.

Chapter V concludes the thesis. It contains an overall summary and conclusions. It also makes recommendations for future study.

#### C. LITERATURE REVIEW

Regression analysis and time-series analysis are two scientific approaches to making attrition forecasts. A wealth of historical research is available concerning the attrition of military forces. Nearly all of this historical research uses regression analysis.

In addition to making forecasts, regression analysis identifies variables that effect attrition. It is useful in identifying the characteristics of who is being lost. This information influences policy-makers who make decisions in an attempt to influence realized attrition.

Yaffee (Yaffee, 2000) describes a time series as "a sequence of observations ordered by a time parameter." The result of a time-series analysis is a just a forecast. No inference of the characteristics of who is being lost can be made.

Rubiano (Rubiano, 1993) argued his use of regression stating "the desire to forecast." Esmann (Esmann, 1984) cites simplicity as his reason for using regression. Time-series analysis could have been used for both studies. Time-series provides the forecast that Rubiano requires. It is also provides the simplicity that Esmann sought.

The research question for both aforementioned studies deals with attrition rates, not characteristics. For this author, the choice of regression or time-series largely depends on what is being asked. If the question is just about attrition, as in this research, time-series is a good approach. If the question is broader, or the analyst expects questions about the characteristics of those lost, regression would be a better approach.

This thesis develops several time series models for predicting officer loss rates by grade and control branch. Dewald (Dewald 1996) conducted a similar time-series analysis of U.S. Army enlisted loss rates.

Although not specifically stated in his thesis, Dewald assumed that enlisted soldiers losses were homogeneous across basic branches. A key difference between this thesis and Dewald's is that the officer population is not assumed to be homogeneous among basic branches. This is a significant difference since predictions about specific populations are often required.

One of the models Dewald considered was the auto-regressive integrated moving average (ARIMA) model. An ARIMA model must be stationary. If the underlying series is not stationary the time series can be differenced to make it stationary. This is the 'I' in ARIMA.

An ARMA (or ARIMA with I=0) would be valid if the underlying series is proven to be stationary. An examination of the correlation and partial correlation plots, generated from the series, is necessary to make a claim of stationarity. The stationarity condition and correlation plot properties were assumed by Dewald but will be examined in detail in this thesis.

The models used in this study are limited in their ability to make predictions beyond one or two periods. Time series forecasts assume the conditions surrounding the forecast remain constant (Yaffee, 2000). Since time-series models make extrapolatory predictions, they should be used cautiously as a tool for making long-term forecasts.

## II. RESEARCH METHODOLOGY

#### A. DATA VALIDATION

The data provided by the Army G-1 for this thesis came from the Army's Total Army Personnel Data Base-Active Officer (TAPDB-AO) database. It contains each gain, promotion and loss transaction that occurred between October 1998 and September 2004; a period of seventy-two months. Each individual record contains numerous variable fields; type of transaction (gain, promotion, loss), social security number, month and year of the transaction, officers basic and control branch, and information on the officer's rank.

Gain transactions record officers who just came onto active duty or returned after a break in service. Promotion transactions record officers' promotions, including their current and previous rank. Loss transactions record the retirement, separation, or death of officers which translate into a reduction in total officer strength. A list of the ninety-two ways an officer can be classified as a loss is contained in appendix A.

Chatfield (Chatfield, 2001) describes the process of data cleaning as examining the quality of the data and considering modifying the data to remove any obvious errors. The TAPDB-AO data provided by the G-1, which contained over 140,000 records, required extensive work in this area. A cursory look at the raw data reveals numerous instances of duplicate or repetitive loss records for the same transaction. A duplicate means that the same exact record exists in the data-set more than once. A repetitive record means that the same record exists in the data for one or more consecutive months. Observations of duplicate and repetitive transactions can be found in gain and promotion records as well. These initial observations had to be corrected before any analysis can begin.

#### 1. Identification of Database Errors

A count of unique social security numbers revealed that only 69% are unique. One would expect some duplication of social security numbers to appear since the data spans six years. For example, a social security number for a second lieutenant which

appears as a gain in October 1998 would be expected to appear with an associated first lieutenant promotion two years later in October 2000, and again with a promotion to captain in October 2002.

As expected, duplications like the one described in the example above are present. However, there are also clearly erroneous instances of multiple records for the same promotion, loss or gain. For example, for a major who separates from the service in January 2000, there should be a corresponding single loss record in the January 2000 data. Yet in many instances the data contains two or more loss records, or additional loss records in the months following. As a result, inclusion rules were developed to clean the data by screening out these obvious errors in the TAPDB-AO data.

## 2. Development of Inclusion Rules

Including the duplicate and repetitive records would lead to biased prediction results. The data had to be cleansed to eliminate any bias and accurately represent true realized losses. To this end, a set of data inclusion rules for gains, promotions and losses was developed to eliminate any duplicate or repetitive observation error. A summary of the data inclusion rules used to eliminate duplicate and repetitive record errors for gains, losses and promotions is outlined below.

#### a. Gains

- Only zero, one, or two gains are allowed per individual.
- If an individual has two gain records, a loss record must seperate.
- If an individual has duplicate gain records in the same month and year, only the first gain record is valid.
- An officer can be gained into any rank.

#### b. Promotion

- Only zero, one, or two promotions are allowed per individual.
- If an individual has a duplicate promotion record in the same month and year, only the first promotion record is valid.
- If an individual has a second promotion record, it must follow the first promotion by at least thirteen months.
- An officer can only be promoted into the next higher rank.

#### c. Losses

- Only zero or one losses are allowed per individual.
- If an individual has duplicate loss records (e.g. same month and year), only the first loss is valid.
- If an individual has repetitive loss records (e.g. consecutive months), only the first one is valid.

#### B. DATA AGGREGATION

The data provided by the Army G-1 consists of individual gain, promotion and loss records from October 1998 to September 2004. This means that the data had to be aggregated in such a way as to capture the net gain or loss by basic branch and grade for each month. Additionally, promotions had to be redefined since they result in a loss to the officer's previous grade and a gain to the officer's new grade.

#### 1. Promotions Redefined

Two new variables, "promotion gain" and "promotion loss" were introduced to accommodate the effects of promotions on net losses. For example, an infantry officer who was promoted from captain to major would be simultaneously classified as an infantry captain loss (promotion loss) and an infantry major gain (promotion gain).

# 2. Aggregation Procedure

'Loss' and 'gain' variables were used in addition to the promotion variables described above. A loss is defined as an individual who separates from the Army by one of the ninety-two reasons listed in appendix A. A gain is defined as an individual who enters or returns to active duty from one of the eleven sources listed in Table 1.

SOURCE	TYPE
USMA	USMA
ROTC-SCHOLARSHIP	ROTC
ROTC	ROTC
OCS-DMG	ocs
OCS	ocs
NATIONAL GUARD STATE OCS	OTHER
DIRECT APPOINTMENT	OTHER
USAFA	OTHER
USNA	OTHER
USMMA	OTHER
OTHER	OTHER

Table 1. Sources of officer gains

Aggregating the data to capture net gains or losses by basic branch and grade for each month is a simple summation of variables. This summation is represented in Equation 2.1 where index i represents the month and index j represents basic branch. A negative result means there is a net gain in strength in month i for basic branch j and a positive result means there is a net loss. Applying this summation procedure to the data

results in a sixty-month time series table for each of the seventeen basic branches. The formula in Equation 2.1 is applied twice, once for captains and once for majors, to produce the respective aggregated loss tables. Applying the formula in Equation 2.1 to the cleansed data results in the aggregated loss tables similar to those displayed below in Table 2. The column headers indicate basic branches. A complete list of basic branch abbreviations is in Table 3. The complete net loss tables for both captains and majors are contained in Appendix B.

Net 
$$Loss_{ij} = Loss_{ij} + PromLoss_{ij} - Gain_{ij} - PromGain_{ij} \quad \forall i \in I, j \in J$$
 (2.1)

Date	AD	AG	AR	ΑV	СМ	EN	FA	FI	IN	MI
10/1/1998	16	5	19	30	4	15	39	3	41	20
11/1/1998	3	-1	-4	7	6	7	4	0	1	5
12/1/1998	12	7	26	16	5	19	27	4	30	40
1/1/1999	13	9	16	23	7	6	13	3	26	40
2/1/1999	5	-1	12	21	-7	30	-6	2	3	4
3/1/1999	17	16	24	25	10	20	38	1	51	32
4/1/1999	12	11	23	37	11	26	41	8	58	53
5/1/1999	8	11	27	12	11	18	52	5	20	33

Table 2. Partial Aggregated Loss Table

AD	Air Defense Artillery
AG	Adjutant General's Corps
AR	Armor
AV	Aviation
CM	Chemical Corps
EN	Corps of Engineers
FA	Field Artillery
FI	Finance Corps
IN	Infantry
MI	Military Intelligence Corps
MP	Military Police Corps
MS	Medical Service Corps
OD	Ordnance Corps
QM	Quartermaster Corps
SC	Signal Corps
SF	Special Forces
TC	Transportation Corps

Table 3. Basic Branch Abbreviations

The aggregated net-losses are separated into training data and test data-sets for both captains and majors. Training data is used to identify the best fitting model and contains the majority of the data (Oct 98-Sept 03). The remaining data (Oct 03-Sept 04) comprises the test set and is used to evaluate how well the best model predicts.

## III. METHODOLOGY

#### A. DATA OBSERVATIONS

#### 1. Initial Data Observations

SAS, version 8.1, is the statistical software package currently in use by the Army G-1. We have chosen SAS to conduct this research since it will facilitate the G-1 in implementing the recommendations.

Creating time-series graphs for each branch and grade is accomplished by writing code in the SAS editor window once the aggregated loss tables are created. Figure 1 contains the SAS code used to create time series plots. Comments (between /\* and \*/) are included to help explain the code. This SAS code generated the graph in Figure 2 for air defense captains. Similar code was used to produce the time-series loss graph for ordnance majors in Figure 3.

```
data Captains;
INFILE 'C:\CaptNoNames.txt' DLM='09'X DSD MISSOVER;
INPUT
AD
     AG
           AR
                 ΑV
                       CM
                             EN
                                  FA FI
                                                    MΙ
                                                          MΡ
                                                                MS
                                              IN
     OD
           QM
                 SC
                       SF
                             TC;
                                         /*creation date variable*/
date=intnx('month','010CT1998'd,_n_-1);
format date monyy5.;
                                       /*specifies format for date*/
symbol i=join c=blue;
                                   /*Use blue line for time series*/
axis1 label=(a=90 'Losses');
                                   /*Label Losses on vertical axis*/
PROC gplot;
                                   /*Plots losses for each branch*/
plot AD*date /vaxis=axis1;
title justify=c 'AD Captain Losses';
run;
QUIT;
```

Figure 1. SAS Code For Creation of Time-Series Plots

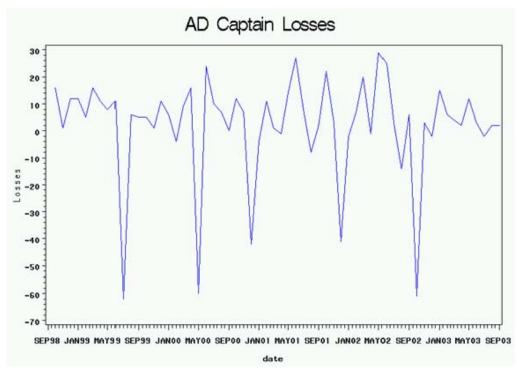


Figure 2. Time-Series Plot of Air Defense Captains' Losses

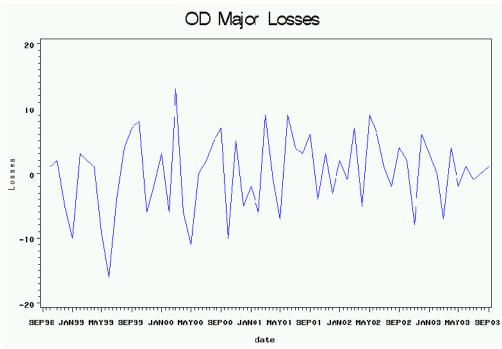


Figure 3. Time-Series Plot of Ordnance Majors' Losses

The time-series plots in appendix C do not lend themselves to intuitive interpretation. The only obvious feature of these graphs is five well-defined downward spikes common to most of the captain graphs. These spikes, indicating a net gain for the

respective branch, are explained by promotion policy. Time in service determines when second lieutenants get promoted to first lieutenant and later promoted to captain. This means that all second lieutenants commissioned in the same month will be promoted to both first lieutenant and later captain at the same time. Those spikes are therefore expected since most commissioning is done in the May and June timeframe.

The majors' time-series graphs do not contain well-defined spikes since promotions to major follows a different policy. Captains are promoted to major from a list. Army requirements determine how many captains from this list get promoted in a given month. Unlike promotion to captain, this requirements based promotion policy prevents large gain spikes from occurring.

#### 2. Detailed Data Observations

Box and Jenkins (Box, 1976) explained stationary as being "characterized by an equilibrium around a constant mean level as well as a constant dispersion around that mean level". In other words a series that has a fixed mean and constant variance is said to be stationary.

Intuition does not provide much information for any of the time-series graphs in Appendix C. There is no obvious seasonality or trend in any of the plots. A student of time-series analysis might suggest that the plots appear roughly stationary. However, a formal test of stationarity is needed to confirm this belief. Stationarity is a necessary condition for many time-series models and must be tested for. Brocklebank (Brocklebank, 2003) suggests using the Dickey-Fuller Unit Root Test to accomplish this task. This test can be conducted in SAS, version 6.12 and newer, through the editor window or in the Time-Series Forecasting System. This test requires information about the auto-regressive properties of the series in question, so correlogram plots need to be generated before the Dickey-Fuller test can be conducted.

# a. Correlogram

The correlogram, considered "one of the most useful tools in time-series analysis" (Chatfield, 2001), assesses time-series behavior. Graphing the correlogram of each time-series provides three key observations. First, it provides a picture from which the auto-regressive parameter, used in many time-series models and necessary to perform the Dickey-Fuller Unit Root Test for stationarity, can be estimated. Second, it provides a

picture from which the moving average parameter, common to many time-series models, can be estimated. Lastly, it provides graphical evidence useful in examining the assumption of a stationarity series.

A SAS-generated correlogram provides autocorrelation and partial-autocorrelation graphs. Figure 4 shows the autocorrelation graph and Figure 5 shows the partial autocorrelation graph for Military Police captains. The two dotted vertical lines to the right and left of zero, often referred to as the bounds of stability, represent two standard deviations from the series mean.

The autoregressive parameter estimate is obtained from the autocorrelation graph. The autocorrelation in Figure 4 shows a time-series that attenuates immediately to within the bounds of stability. This provides three results. First, the autoregressive parameter is zero. This is the case when, "[a]part from the value at lag zero, which is always one and tells us nothing, the autocorrelations all lay inside the bounds of stability (Chatfield, 2001)". Second, it provides evidence that the series is stationary, since autocorrelations for non-stationary series tend to attenuate slowly or even increase. Lastly, there is no seasonality present. Spikes in the autocorrelation graph would be present if seasonality existed: every three lags for quarterly seasonality or twelve for annual seasonality (Yaffee, 2000).

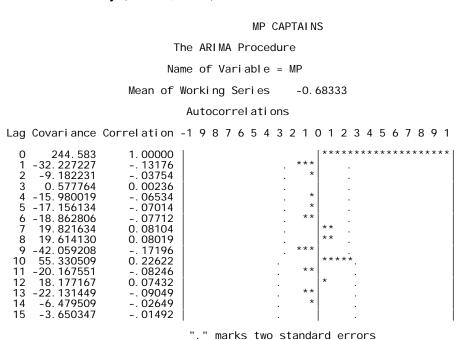


Figure 4. Autocorrelation Plot for Military Police Captains

The partial autocorrelation graph in Figure 5 assists in identifying the moving average parameter. This graph provides two useful results. First, the moving average parameter is zero since no lags are necessary to move inside unity. Second, it also supports the belief that the series is stationary since no significant spikes are present at any lag.

The Dickey-Fuller Unit Root Test code in Appendix E generates correlograms for the other basic branches. An analysis of these correlograms supports similar findings with respect to autoregressive parameters, stationarity and moving average parameters for all basic branches.

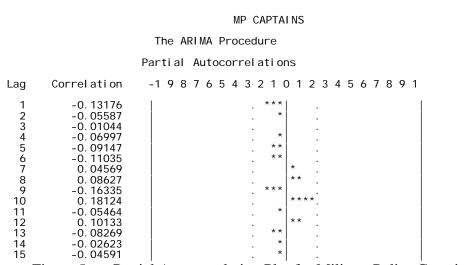


Figure 5. Partial Autocorrelation Plot for Military Police Captains

## b. Dickey-Fuller Unit Root Test

All results thus far indicate that we are dealing only with stationary series. An additional approach, the Dickey-Fuller Unit Root Test, is produced by the SAS procedure PROC ARIMA. The complete code is in Appendix E. This code produced the Dickey-Fuller Unit Root Tests result for air defense majors shown in Figure 6.

**AD Majors** 

Dickey-Fuller Unit Root Tests	Di cke	y-Ful I	ler	Uni t	Root	Tests
-------------------------------	--------	---------	-----	-------	------	-------

Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean Single Mean Trend	Ö	-60. 8952 -60. 8961 -64. 7979	<. 0001 0. 0005 0. 0001	-7. 86 -7. 80 -8. 17	<. 0001 0. 0001 <. 0001		0. 0010 0. 0010
		Figure 6	6. Dick	ev-Fulle	r Stationar	v Test	

Notice that the lag parameter, identified by observing the autocorrelation plot in Figure 6, is zero. In the code, this is accomplished by specifying adf=(0) where 0 is the autoregressive parameter identified from the autocorrelation plot. Rho represents the coefficient of the lagged response variable. Tau tests whether the lagged term is significant (Yaffee, 2000). The F statistic tests intercept and mean conditions. The F statistic is ignored here since we are only interested in stationarity results and their significance which we determine from Rho and Tau respectively, (Brocklebank, 2003). A time-series with Rho and Tau probabilities less than the generally accepted .05 level of significance is considered stationary (Yaffee, 2000).

The Dickey-Fuller Unit Root Test performs three types of tests simultaneously. The characteristics of the time-series in question will dictate which type of test is needed to conclude a series is stationary. The *Zero Mean* type is used for a time-series with random walk and without drift or trend. The *Single Mean* type is used for a series with random walk and drift but without trend. *Trend* is used when there is random walk and drift with trend.

Trend is defined as "a regular, slowly evolving change in the series level" (Brocklebank, 2003). We can eliminate the *Trend* type test since none of the time-series in appendix C exhibits this characteristic.

Drift is defined as "random variation about a non-zero level" (Yaffee, 2000). We can eliminate the *Single Mean* type test since all the time-series exhibit variation about zero.

The type of test needed to look for stationarity conditions is the *Zero Mean* type. Figure 5 clearly shows significant *Rho* and *Tau* probabilities for this type which indicates a stationary series. Appendix F contains similar Dickey-Fuller Unit Root Test results for all time-series considered in this thesis.

#### B. SAS TIME SERIES FORECASTING SYSTEM

#### 1. Overview Of SAS TSFS

Internal to SAS version 8.1 is a windows-based program called the Time Series Forecasting System or TSFS. TSFS is a powerful program capable of automatically fitting models from forty-two different time series and identifying the best fit model in seconds. TSFS also provides statistics of fit and diagnostic tools, such as the correlogram, in a windows-based point and click environment.

#### 2. Considered Models

SAS TSFS allows the user to select any number of the forty-two time-series models for analysis. However, previous observations of the data allow the dismissal of many of these models.

All time-series plots in this thesis contain some negative values. This allows the removal of any natural log models for obvious reasons. An interpretation of the correlogram plots (autocorrelation and partialautocorrelation), combined with the Dickey-Fuller Unit Root test for stationarity allows elimination of complicated Auto-Regressive Integrated Moving Average (ARIMA) models. Simple ARIMA models, such as seasonal exponential smoothing which is an ARIMA (0,1,1), were left for TSFS to consider. The ten models that remain viable for further analysis are:

- Seasonal Exponential Smoothing
- Winters Method-Additive
- Mean
- Simple Exponential Smoothing
- Double (Brown) Exponential Smoothing
- Linear Trend
- Linear (Holt) Exponential Smoothing
- Dampened Trend Exponential Smoothing
- Seasonal Dummy
- Linear Trend with Seasonal Terms

#### C. EVALUATING MODEL FIT

There are many different error measures available in TSFS to evaluate and identify which time-series model fits best. Selection of an appropriate error measure is more art than science. There is no single 'best' measure. Two commonly used time-series error measures were considered for adoption in this thesis: Mean Square Error and

Akaike Information Criterion. The formulas for MSE and AIC is given in Equations 3.1 and 3.2 respectively.

$$MSE = \frac{SSE}{T - 1} \tag{3.1}$$

$$AIC = -2LOG(max likelihood) + 2k$$
 (3.2)

where SSE = Sum of Squared Error

T = number of observations

k = number of parameters estimated

## 1. Mean Square Error

Mean Square Error (MSE), shown in Equation 3.1, is one of the most commonly used measures in statistics and time-series analysis. It measures the average prediction error. There are two drawbacks to using MSE or sum of squares (SSE) as evaluation measures. Considered jointly, these drawbacks resulted in dismissing the idea of using MSE as the model selection criterion.

First, MSE and SSE severely penalize outliers in the data. Nearly all of the captain time-series plots exhibit large spikes, or outliers. Second, using MSE as the selection criterion places no penalty on the number of parameters used in the model formulation. A model evaluation measure that avoids these problems is beneficial.

#### 2. Akaike Information Criterion

Because of the issues with using MSE, a "more sophisticated model-selection statistic is generally preferred (Chatfield, 2001)". Akaike's Information Criterion (AIC), shown in Equation 3-2, is a commonly used evaluation statistic that avoids the pitfalls of MSE.

AIC is less sensitive to outlying data than MSE and considers the number of parameters in the model. AIC balances precision of fit against the number of parameters included in the model (Brocklebank, 2003). AIC selects the best fitting model, "as measured by the likelihood function, subject to a penalty term that increases with the number of parameters fitted in the model" (Chatfield, 2001). This penalty, which increases as parameters are added to the model, prevents over-fitting. As a result, AIC

will choose the best-fitting model with the minimum number of parameter estimates. The best model will have the smallest AIC.

### IV. ANALYSIS OF RESULTS

#### A. OVERVIEW

This chapter gives the results obtained from the SAS Time-Series Forecasting System (TSFS). Section B presents two models, from among the ten considered, that TSFS clearly identified as having the best "fit" using AIC as the selection criterion. The three best-fit models identified by TSFS are presented in sections C and D for captains and majors respectively. Section E contains a summary of results and discussion of why the AIC scores are so similar for seasonal exponential smoothing and the Winters additive method.

It is easy to get confused when looking at the computations behind time-series analysis. Notation is usually the root of this confusion. To assist the reader, a summary of the notation used in the time-series calculations can be found in Figure 7.

- $x_t$  observed loss value at time t
- $\hat{x}_{t+s}$  predicted loss value s periods from time t
- $L_t$  Level value at time t
- $T_t$  Trend value at time t
- S, Seasonal value at time t
- $\alpha$  Level smoothing constant
- $\beta$  Trend smoothing constant
- γ Season smoothing constant

Figure 7. Notation

#### B. FORECAST METHODS

Two of the ten viable time-series models presented earlier stood out from the rest. Those two models are seasonal exponential smoothing and Winters method-additive. In every considered time-series, these two models had the best and second-best fits.

#### 1. Seasonal Exponential Smoothing

The seasonal exponential smoothing model was selected by TSFS as having the best fit in thirty-one of thirty-four instances. In the three series in which seasonal exponential smoothing did not have the best fit, it had the second-best fit. *Level* and

seasonality smoothing equations are used in seasonal exponential smoothing to generate predictions about future observations. Alpha ( $\alpha$ ) and gamma ( $\gamma$ ) are numeric smoothing constants with values between zero and one chosen in an optimal way by TSFS. Alpha and gamma were both determined to be .001 by TSFS.

As seen in equation 4.1, the level term,  $L_{t+1}$ , is calculated in three steps. First, the previous seasonal value  $(S_{t-s})$  is subtracted from the current observation  $(x_t)$  and multiplied by the numeric constant alpha. Second,  $(1-\alpha)$  is multiplied by the current level value  $(L_t)$ . Finally, the results from steps one and two are added to determine the value of  $L_{t+1}$ .

$$L_{t+1} = \alpha (x_t - S_{t-s}) + (1 - \alpha) L_t$$

$$S_{t+1} = \gamma (x_{t+1} - L_{t+1}) + (1 - \gamma) S_{t+1-s}$$

$$\hat{x}_{t+1} = L_{t+1} + S_{t-t+1-s}$$
(4.1)
$$(4.2)$$

The seasonal term in equation 4.2,  $S_{t+1}$ , is calculated after the actual value of  $x_{t+1}$  is known. It too is calculated in three steps. First, the previously calculated  $L_{t+1}$  is subtracted from  $x_{t+1}$  and multiplied by gamma. Second,  $(1 - \gamma)$  is multiplied by the seasonal value for this month from one year ago  $(S_{t+1-s})$ . Finally, the results from steps one and two are added to determine the value of  $S_{t+1}$ .

Predictions from the seasonal exponential smoothing method are made using equation 4.3. A prediction for the next period is made by summing the previously determined level and seasonal values of  $L_{t+I}$  and  $S_{t+I-s}$ .

For example, suppose an estimate of next period's Air Defense captain losses is desired using seasonal exponential smoothing. Appendix B shows that the data spans sixty months, so t is 60.  $x_{60}$ , the current observed losses, is shown to be 2. The data is believed to have twelve month seasonality which means s equals twelve.

The first step in predicting losses for  $x_{61}$  is to calculate  $L_{t+1}$  ( $L_{61}$ ).  $S_{t-s}$  ( $S_{60-12}$ ) and  $L_t$  ( $L_{60}$ ) were determined to be .7684 and 2.078 respectively. Subtracting the previous seasonal value of .7684 from the current  $x_{60}$  observation of 2 and multiplying by the given alpha of .001 arrives at a solution of 2.074 for  $L_{t+1}$ .( $L_{61}$ ).

A loss prediction for Air Defense captains in the sixty-first period can now be made. Adding the value for  $L_{t+1}$  ( $L_{61}$ ) to the previously determined seasonal level  $S_{t+1-s}$  ( $S_{60+1-12}$ ) gives the predicted Air Defense captain losses for period  $X_{61}$  as -1.4.

#### 2. Winter's Method-Additive

Winters additive method is the current forecasting technique used by the strength analysis and forecasting branch of the Army G-1. Like seasonal exponential smoothing, it too was frequently selected by TSFS as having the best fit. Winters method-additive is generally referred to as the Holt-Winters method. Winters method-additive bears a striking similarity to seasonal exponential smoothing model. The difference between the two models is an additional parameter, *trend*, in the Winters-additive model. *Level*, *trend*, and *seasonality* smoothing equations are given in equations 4.4, 4.5, and 4.6 respectively and are solved in a similar manner as the seasonal exponential smoothing equations. The recursive equation used to make predictions about future observations is in equation 4.7.

$$L_{t+1} = \alpha (x_t - S_{t-s}) + (1 - \alpha) (L_t + T_t)$$
 (4.4)

$$T_{t+1} = \beta (L_{t+1} - L_t) + (1 - \beta) T_t$$
 (4.5)

$$S_{t+1} = \gamma (x_{t+1} - L_{t+1}) + (1 - \gamma) S_{t+1-s}$$
 (4.6)

$$\hat{x}_{t+1} = L_{t+1} + T_{t+1} + S_{t+1-s} \tag{4.7}$$

TSFS optimally produces the optimal values of  $\alpha$ ,  $\beta$ , and  $\gamma$ , and automatically calculates equations 4.1 through 4.7 making hand calculations unnecessary. For the analyst however, an understanding of what and how TSFS is calculating in the background is necessary when explaining forecasted results to decision makers.

### C. CAPTAINS' RESULTS

Table 4 shows the top three 'best-fit' models for captains. The single most striking result is the dominance of seasonal exponential smoothing as the best fitting model in sixteen of the seventeen branches. Just as remarkable is the dominance of Winters-additive and the mean model as the second and third best fitting respectively.

Another not so apparent result shown in table 4 is the similarity of the AIC scores. In nearly all branches, the first and second choice models have AIC scores within one percent. Such similar AIC scores could result in indifference when selecting which of the two methods to use.

Branch	1st Model Choice	AIC	2nd Model Choice	AIC	3rd Model Choice	AIC
		Score		Score		Score
AD	Seasonal Expo Smoothing	339.5	Winters-Additive	341.2	Mean	348.0
AG	Seasonal Expo Smoothing	336.4	Winters-Additive	338.1	Mean	347.9
AR	Seasonal Expo Smoothing	444.7	Winters-Additive	446.7	Mean	452.6
AV	Seasonal Expo Smoothing	454.8	Winters-Additive	456.8	Mean	463.4
CM	Seasonal Expo Smoothing	247.5	Winters-Additive	248.5	Mean	256.3
EN	Seasonal Expo Smoothing	439.3	Winters-Additive	441.4	Mean	450.2
FA	Seasonal Expo Smoothing	461.2	Winters-Additive	462.9	Mean	472.2
FI	Seasonal Expo Smoothing	211.0	Winters-Additive	213.2	Mean	221.8
IN	Seasonal Expo Smoothing	495.6	Winters-Additive	497.5	Mean	504.1
MI	Seasonal Expo Smoothing	458.1	Winters-Additive	459.4	Mean	465.4
MP	Seasonal Expo Smoothing	316.1	Winters-Additive	317.6	Mean	325.2
MS	Seasonal Expo Smoothing	364.6	Winters-Additive	366.1	Mean	381.2
OD	Seasonal Expo Smoothing	358.4	Winters-Additive	359.7	Mean	364.1
QM	Seasonal Expo Smoothing	379.2	Winters-Additive	380.1	Mean	387.6
SC	Seasonal Expo Smoothing	414.7	Winters-Additive	415.9	Mean	421.6
SF	Winters-Additive	167.8	Seasonal Expo Smoothing	170.4	Linear Trend Seasonal	186.8
TC	Seasonal Expo Smoothing	346.3	Winters-Additive	348.1	Mean	354.8

Table 4. Captains' AIC Result Summary

### D. MAJORS' RESULTS

Table 5 shows the top three 'best-fit' models for majors. A close observation of AIC results leads to a similar conclusion of being indifferent between the first- and second-choice models. Seasonal exponential smoothing is the best-fitting model for fifteen of the seventeen branches with Winters-additive model chosen as the best for the remaining two branches. The opposite is true for the second-choice model with Winters-additive being preferred twelve times and seasonal exponential smoothing being preferred five times.

Branch	1st Model Choice	AIC Score 2nd Model Choice		AIC Score	3rd Model Choice	AIC Score
AD	Seasonal Expo Smoothing	199.5	Winters-Additive	199.7	Linear Trend	217.2
AG	Seasonal Expo Smoothing	193.7	Winters-Additive	194.8	Mean	211.9
AR	Seasonal Expo Smoothing	272.8	Winters-Additive	274.3	Mean	297.8
AV	Seasonal Expo Smoothing	311.9	Winters-Additive	313.8	Mean	341.3
CM	Seasonal Expo Smoothing	155.6	Winters-Additive	156.6	Mean	170.4
EN	Seasonal Expo Smoothing	259.8	Winters-Additive	261.8	Mean	284.7
FA	Seasonal Expo Smoothing	293.7	Winters-Additive	294.7	Mean	323.2
FI	Winters-Additive	62.3	Seasonal Expo Smoothing	66.7	Linear Trend	89.5
IN	Seasonal Expo Smoothing	327.1	Winters-Additive	328.8	Mean	348.9
MI	Seasonal Expo Smoothing	335.1	Winters-Additive	335.4	Linear Trend	349.6
MP	Seasonal Expo Smoothing	181.1	Winters-Additive	181.9	Mean	197.3
MS	Seasonal Expo Smoothing	310.2	Winters-Additive	312.2	Mean	317.2
OD	Seasonal Expo Smoothing	253.1	Winters-Additive	253.3	Mean	270.4
QM	Seasonal Expo Smoothing	262.4	Winters-Additive	262.7	Linear Trend	284.8
SC	Winters-Additive	278.4	Seasonal Expo Smoothing	278.6	Linear Trend	296.2
SF	Seasonal Expo Smoothing	199.7	Winters-Additive	201.7	Mean	226.4
TC	Seasonal Expo Smoothing	182.7	Winters-Additive	183.4	Mean	200.3

Table 5. Majors' AIC Result Summary

#### E. PREDICTIVE POWER

Seasonal exponential smoothing and Winters method-additive provide nearly indistinguishable 'best' fits for our training data. However, no claim can be made to their predictive power. Having the best AIC score tells us little about how well the model predicts. Comparing observed values in the test set against predicted values from the seasonal exponential smoothing model provides such insight.

Figures 8 and 9 present correlation plots of predicted to observed values for captains and majors respectively. The solid diagonal line represents perfect correlation or a theoretical perfect prediction line. Data points on the line represent correct predictions. Data points off the line represent observations that were incorrectly predicted.

The predicted net-losses of captains in 2004 is shown to be 21% correlated to the observed net-losses in the test set. Only one branch, MI, is greater than 50% correlated. This low correlation is partly related to unequally distributed large gain spikes that characterize most of the captain time-series plots. The correlation of each basic branch for captains is given in Table 7.

The correlation of predicted to observed net-losses for majors is shown to be 52%. Eleven of the seventeen basic branches are greater than 50% correlated. The correlation of each basic branch for majors is given in Table 8.

#### Observed vs. Predicted Captains, 2004

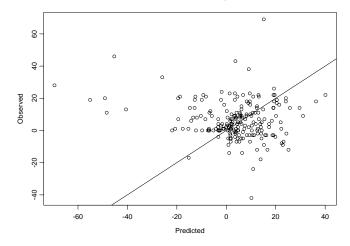


Figure 8. 2004 Captain Correlation Plot

۸Β	0.08	EN	0.21	MD	0.27	QE.	0 11
AD	0.06	LIN	0.51	IVIE	0.27	SF	0.11
AG	0.11	FA	0.12	MS	0.33	TC	0.21
AR	0.08	FI	0.14	OD	0.13		
AV	0.21	IN	0.27	QM	0.35		
СМ	0.13	MI	0.55	SC	0.29		

Table 6. 2004 Captain Correlation by Basic Branch

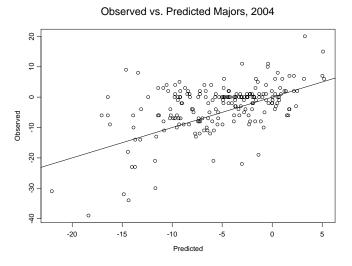


Figure 9. 2004 Major Correlation Plot

0.16	EN	0.67	MP	0.03	SF	0.63
0.75	FA	0.62	MS	0.53	TC	0.52
0.22	FI	0.02	OD	0.61		
0.65	IN	0.43	QM	0.34		
0.67	MI	0.54	SC	0.66		
	0.75 0.22 0.65	0.75 FA 0.22 FI 0.65 IN	0.75 FA 0.62 0.22 FI 0.02 0.65 IN 0.43	0.75 FA 0.62 MS 0.22 FI 0.02 OD 0.65 IN 0.43 QM		0.22 FI 0.02 OD 0.61 0.65 IN 0.43 QM 0.34

Table 7. 2004 Major Correlation by Basic Branch

#### F. SUMMARY

Ten time-series models were produced in TSFS for each of thirty-four combinations of basic branch and grade (captain and major). For each combination the ten models were evaluated using the AIC (Akaike Information Criterion) and the three best reported.

The captains' TSFS results are shown in Table 4. With the exception of special forces branch, seasonal exponential smoothing and Winters method-additive are the best and second best fitting models respectively. The opposite is true in special forces branch where Winters method is the best fitting and seasonal exponential smoothing the second best. In every series, AIC scores between the first and second choice models vary less than one-half a percent. AIC scores show that the fit of the top two fitting models is nearly indistinguishable.

The majors' TSFS results are shown in Table 5. The results are nearly the same as those found in the captains'. In every series, seasonal exponential smoothing and Winters method-additive are the top two fitting models. Just as in the captains' results, the fit of these two models is nearly indistinguishable. The AIC scores between the first and second choice models vary less than one percent.

These best fitting models have weak predicting power. Predictions generated from the seasonal exponential smoothing model for 2004 were compared to the corresponding observed values in our test set. The observed and predicted values for captains have a correlation of .21; for majors the correlation is .52. Correlation results for each basic branch are shown in Tables 6 and 7.

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### V. CONCLUSION

#### A. SUMMARY

Accurate prediction of officer loss behavior benefits decision and policy makers alike. An inaccurate prediction of officer strength affects the number of personnel authorizations, the Army's budget, and the necessary number of accessions. Imbalances of branches and career fields affect the Army's combat readiness as a whole. An accurate picture of officer loss behavior is especially sought for officers in the grades of O-3 and O-4.

Captain and major losses, by basic branch, from October 1998 to September 2004 were aggregated into time-series. Ten different time-series forecasting techniques were applied to each of thirty-four series through SAS TSFS to identify which models fit best. The forecasting techniques applied were seasonal exponential smoothing, Winters method-additive, mean, simple exponential smoothing, double exponential smoothing, linear trend, linear (Holt) exponential smoothing, dampened trend exponential smoothing, seasonal dummy and linear trend with seasonal term.

Akaike's Information Criterion was used to evaluate the fit of each of the ten models. Two models, seasonal exponential smoothing and Winters method-additive, distinguished themselves from the others. These two models had the best fits in every series.

However, these best fitting models have week predicting power. Predictions from the seasonal exponential smoothing model were compared to the observed values in our test set. The predictions for captain net-losses are 21% correlated and majors 52% correlated.

#### B. OVERALL CONCLUSIONS

There is no universal 'best-fit' forecasting technique. Seasonal exponential smoothing and Winters-method additive are proven to be the best fitting models for the TAPDB-AO data. Using Akaike's Information Criterion (AIC) as a selection statistic, seasonal exponential smoothing and Winters method-additive are shown to have indistinguishable fits.

Winters method-additive, the current technique used by the Strength Analysis and Forecasting Branch, Army G-1, is validated. Although seasonal exponential smoothing is less complex, having one less parameter, the increase in fit as measured by AIC is negligible.

Officers who utilize time-series techniques to make net-loss predictions are cautioned from expecting too much. The best prediction model was only 52% correlated to the observed data. Time-series techniques should continue to be applied despite these weak correlations until another model is proven better.

#### C. RECOMMENDATIONS FOR FURTHER STUDY

A comparison of the results of multiple regression and time-series is worth investigating. Such a study would require the collection of external monthly econometric variables such as gross domestic product, unemployment rate, durable good orders, etc. Multiple regression may achieve better fitting models than the time-series shown here.

# APPENDIX A LOSS CODES

SPD Code	Narrative Reason	AR 635-5-1 Category
BDK	Military Personnel Security Program	Resignation
BHK	Substandard Performance	Resignation
BNC	Unacceptable Conduct	Resignation
BRA	Homosexual Act	Resignation
BRB	Homosexual Admission	Resignation
BRC	Homosexual Marriage (or Attempt)	Resignation
DFS	In Lieu of Trial by Court-Martial	Resignation
FCA	Early Release Program-Voluntary Separation Incentive	Resignation
FCB	Early Release Program-Special Separation Benefit	Resignation
FDF	Pregnancy or childbirth	Resignation
FDL	Ecclesiastical Endorsement	Resignation
FFW	Failed Medical/Physical Procurement Standards	Resignation
FHC	Immediate Enlistment or Reenlistment	Resignation
FHG	Dismissal, No Review	Resignation
FND	Miscellaneous/General Reasons	Resignation
JCC	Reduction in Force	Involuntary discharge
JDK	Military Personnel Security Program	Involuntary discharge
JDL	Ecclesiastical Endorsement	Involuntary discharge
JDN	Lack of Jurisdiction	Involuntary discharge
JFG	Competent Authority, Without Board Action	Involuntary discharge
JFL	Disability, Severance Pay	Involuntary discharge
JFM	Disability, Existed Prior to Service, Physical Evaluation Board	Involuntary discharge
JFP	(PEB) Disability, Not in Line of Duty	Involuntary discharge
JFR	Disability, Other	Involuntary discharge Involuntary discharge
JFW	Failed Medical/Physical Procurement Standards	Involuntary discharge
JGB	Non-Selection, Permanent Promotion	Involuntary discharge
JHF	Failure to Complete Course of Instruction	Involuntary discharge
JHK	Substandard Performance	Involuntary discharge
JJD	Court Martial	Involuntary discharge
JKB	Misconduct	Involuntary discharge
JNC	Unacceptable Conduct	Involuntary discharge
JND	Miscellaneous/General Reasons	Involuntary discharge
JRA	Homosexual Act	Involuntary discharge
JRB	Homosexual Admission	Involuntary discharge
JRC	Homosexual Marriage (or Attempt)	Involuntary discharge
KCA	Early Release Program-Voluntary Separation Incentive	Voluntary discharge
KCA	Early Release Program-Special Separation Benefit	Voluntary discharge
KCC	Reduction in Force	Voluntary discharge
KCM	Conscientious Objector	Voluntary discharge
KCQ	Surviving Family Member	Voluntary discharge
KDK	Military Personnel Security Program	Voluntary discharge
KFF	Secretarial Authority	Voluntary discharge
KHK	Substandard Performance	Voluntary discharge
KNC	Unacceptable Conduct	Voluntary discharge
KND	Miscellaneous/General Reasons	Voluntary discharge
MID	WIISCOMMICOUS/OCHCIM REASONS	voluntary discharge

		Involventour valence from active duty
LBB	Maximum Age	Involuntary release from active duty (REFRAD) or transfer
	•	Involuntary release from active duty
LBC	Maximum Service or time in Grade	(REFRAD) or transfer Involuntary release from active duty
LBK	Completion of Required Active Service	(REFRAD) or transfer
1.00		Involuntary release from active duty
LCC	Reduction in Force	(REFRAD) or transfer Involuntary release from active duty
LFH	Failure to Accept Regular Appointment	(REFRAD) or transfer
LGB	Non-Selection, Permanent Promotion	Involuntary release from active duty (REFRAD) or transfer
Lob	•	Involuntary release from active duty
LGC	Non-Selection, Temporary Promotion	(REFRAD) or transfer Involuntary release from active duty
LGH	Non-Retention on Active Duty	(REFRAD) or transfer
	D' ' LA '' A HAD'	Involuntary release from active duty
LHH	Dismissal, Awaiting Appellate Review	(REFRAD) or transfer Involuntary release from active duty
LND	Miscellaneous/General Reasons	(REFRAD) or transfer
MBK	Completion of Required Active Service	Voluntary REFRAD or transfer
MBM	Insufficient Retainability (Economic Reasons)	Voluntary REFRAD or transfer
MCA	Early Release Program-Voluntary Separation Incentive	Voluntary REFRAD or transfer
MCB	Early Release Program-Special Separation Benefit	Voluntary REFRAD or transfer
MCC	Reduction in Force	Voluntary REFRAD or transfer
MCF	To Attend School	Voluntary REFRAD or transfer
MDB	Hardship	Voluntary REFRAD or transfer
MDF	Pregnancy or Childbirth	Voluntary REFRAD or transfer
MFF	Secretarial Authority	Voluntary REFRAD or transfer
MGJ	Request for Extension of Service Denied	Voluntary REFRAD or transfer
MGP	Interdepartmental Transfer	Voluntary REFRAD or transfer
MGU	Enrollment in a Service Academy	Voluntary REFRAD or transfer
MHC	Immediate Enlistment or Reenlistment	Voluntary REFRAD or transfer
MND	Miscellaneous/General Reasons	Voluntary REFRAD or transfer
PKB	Misconduct	Dropped from the rolls of the Army
PKF	Misconduct	Dropped from the rolls of the Army
RBD	Sufficient Service for Retirement	Retirement
RBE	Voluntary Early Retirement	Retirement
RCC	Reduction in Force	Retirement
RDL	Ecclesiastical Endorsement	Retirement
RHK	Substandard Performance	Retirement
RNC	Unacceptable Conduct	Retirement
SBB	Maximum Age	Retirement
SBC	Maximum Service or Time in Grade	Retirement
SBE	Involuntary Early Retirement	Retirement
SCC	Reduction in Force	Retirement
SFJ	Disability, Permanent	Retirement
SFK	Disability, Temporary	Retirement
SGB	Non-Selection, Permanent Promotion	Retirement
SHK	Substandard Performance	Retirement
SNC	Unacceptable Conduct	Retirement
VBK	Completion of Required Active Service	Retirement
WFJ	Disability, Permanent	Retirement
WFK	Disability, Temporary	Retirement
WFQ	Disability, Aggravation	Retirement
YDN	Lack of Jurisdiction	Release from military control

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# APPENDIX B AGGREGATED LOSS TABLES

# A. AGGREAGED CAPTAINS' LOSSES

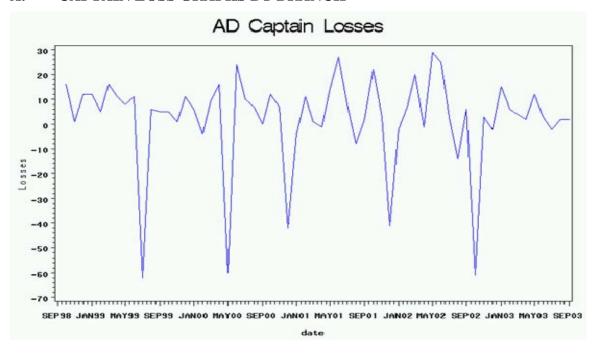
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12/1/1998	12	7	26	16	5	19	27	4	30	40	13	49	24	21	19	13	8
1/1/1999	13	9	16	23	7	6	13	3	26	40	10	9	25	33	15	18	17
2/1/1999	5	-1	12	21	-7	30	-6	2	3	4	0	-21	-3	-3	19	10	5
3/1/1999	17	16	24	25	10	20	38	1	51	32	16	17	22	12	14	22	8
4/1/1999	12	11	23	37	11	26	41	8	58	53	10	5	17	36	39	11	22
5/1/1999	8	11	27	12	11	18	52	5	20	33	8	23	22	27	35	14	9
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7/1/1999	-63	-36	-144	-153	-30	-120	-144	-16	-218	-141	-45	-55	-64	-68	-100	6	-71
8/1/1999	6	7	17	20	1	17	29	3	28	24	6	42	10	9	16	4	16
9/1/1999	3	-4	-7	-4	-1	-1	-12	-1	-9	0	1	18	-19	-7	8	2	-2
10/1/1999	5	4	5	17	6	14	12	2	13	13	0	26	17	8	11	4	7
11/1/1999	-1	7	10	8	7	26	15	0	3	24	8	-16	17	21	28	9	17
12/1/1999	12	12	27	24	2	6	18	9	24	24	8	10	11	9	21	5	15
1/1/2000	6	13	10	12	7	8	17	1	17	10	10	-1	7	21	14	12	13
2/1/2000	-4	-5	-2	5	5	3	-1	1	-3	2	-8	-7	0	5	-9	11	-8
3/1/2000	9	7	41	26	0	30	24	3	43	18	5	19	4	10	14	22	3
4/1/2000	16	6	13	25	11	7	37	4	35	36	2	5	31	22	30	17	15
5/1/2000	-60	-49	-152	-147	-9	-116	-121	-5	-222	-120	-30	17	-36	-54	-70	7	-39
6/1/2000	23	7	33	-4	11	44	57	-2	68	37	2	-28	12	7	33	7	11
7/1/2000	11	11	22	20	1	19	28	4	27	24	11	-44	10	18	28	5	11
8/1/2000	7	6	1	6	-1	1	8	-2	0	18	-13	47	1	4	7	7	-6
9/1/2000	1	5	13	23	2	3	16	2	18	24	6	38	10	1	23	6	4
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11/1/2000	9	8	19	18	3	9	15	4	22	23	8	42	12	19	28	12	8
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3/1/2001	3	-9	23	15	1	31	15	3	21	36	0	-14	10	1	20	12	10
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12/1/2001	-40	-70	-116	-176	-22	-150	-163	-16	-205	-139	-32	-28	-53	-71	-65	6	-63
1/1/2002	-2	-4	13	27	2	17	15	2	11	19	16	8	8	6	11	3	5
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5/1/2002	29	10	59	36	9	68	60	9	73	21	-2	37	31	25	29	13	15
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8/1/2002	-12	5	3	10	3	1	17	0	5	-1	-2	1	7	-15	-5	13	-6
9/1/2002	6	-2	11	12	-3	14	-2	-5	10	0	3	3	3	2	-13	6	-1
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6/1/2003	6	-1	-2	-15	6	4	1	0	5	8	-7	-46	1	-15	10	7	-2
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8/1/2003	2	1	4	1	1	4	1	1	5	3	7	0	5	3	2	0	5
	2	2								2				7		5	
9/1/2003			18	25	0	24	9	1	18		-1	14	8		12		24
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12/1/2003	8	1	13	11	12	20	19	2	28	46	6	12	9	20	21	2	7
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2/1/2004	1	-1	7	6	-2	-2	4	-3	-3	16	-5	1	1	-3	-9	9	3
3/1/2004	10	15	16	5	4	9	26	1	20	14	7	3	14	21	14	11	8
4/1/2004	-3	-7	2	17	-7	23	-3	-9	18	-18	-14	-5	-24	-42	-12	9	-14
5/1/2004	8	1	19	14	11	11	4	-1	19	3	-4	18	22	7	7	13	9
6/1/2004	2	0	14	2	9	14	22	4	18	1	6	9	0	4	9	11	5
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8/1/2004	4	8	18	22	4	21	18	3	43	23	4	-12	8	16	10	7	7
9/1/2004	2	-5	-3	-3	1	1	3	2	-2	-5	-5	69	-7	5	-12	2	8
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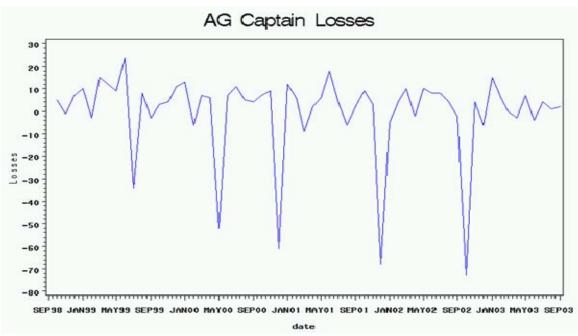
# B. AGGREGATED MAJORS' LOSSES

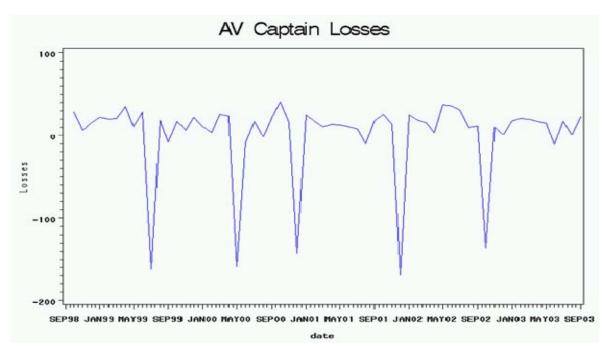
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12/1/1998	-10	-1	-17	-11	-2	-12	-17	-3	-21	-28	-7	-42	-15	-13	-10	-10	-4
1/1/1999	-13	-2	-3	-12	-4	-8	-6	-4	-17	-22	-7	-2	-13	-25	-15	-11	-13
2/1/1999	-6	-2	-18	-25	-2	-21	-7	1	-14	-11	-4	-4	0	0	-23	-8	-8
3/1/1999	-7	-10	-17	-18	-6	-12	-26	0	-28	-7	-8	-7	-8	-3	3	-17	-4
4/1/1999	-7	-4	-10	-15	-3	-13	-19	-6	-25	-27	-4	-6	-9	-17	-12	-5	-9
5/1/1999	-4	-7	-8	-12	-12	-5	-22	-4	-9	-20	-4	-9	-12	-15	-29	-5	-11
6/1/1999	-1	-20	-12	-21	-2	-1	-2	0	-11	-18	-4	-2	-16	-9	-13	-7	-10
7/1/1999	-1	-8	-7	-9	1	-6	-9	-2	-20	-5	-6	-28	-4	-2	1	-5	-2
8/1/1999	0	3	5	7	0	2	5	0	5	5	3	-1	3	6	7	0	2
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10/1/1999 11/1/1999	0	0 -10	-19	-13	1 -4	-20	5 -24	0 -1	6 -14	-25	0 -10	-3 -26	0 -18	0 -21	-26	-8	0 -13
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3/1/2000	-6	-4	-25	-19	-1	-22	-24	0	-35	-1	0	-16	-1	-1	-2	-15	1
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7/1/2000	4	3	5	6	0	5	5	1	9	8	1	3	2	3	5	3	4
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6/1/2003	-2	-5	2	-4	-1	1	-9	0	-7	-11	-2	-8	-9	-3	-9	-5	-5
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9/1/2003	-5	2	-13	2	-1	-10	-12	1	-16	1	0	-8	-2	0	2	-1	3
10/1/2003	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
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8/1/2004	-2	0	-6	-4	3	-10	-6	1	-19	10	-4	0	-1	-2	7	0	2
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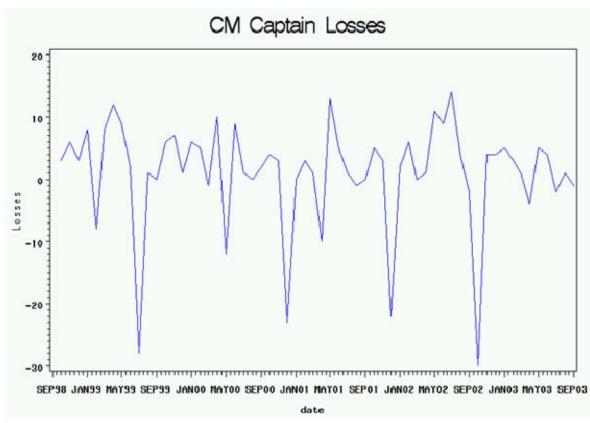
# APPENDIX C LOSS GRAPHS

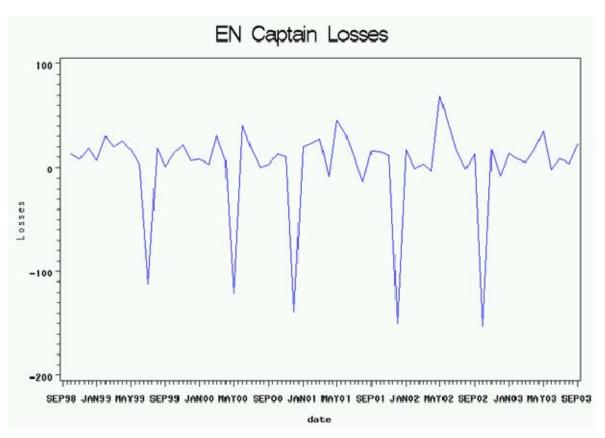
### A. CAPTAIN LOSS GRAPHS BY BRANCH

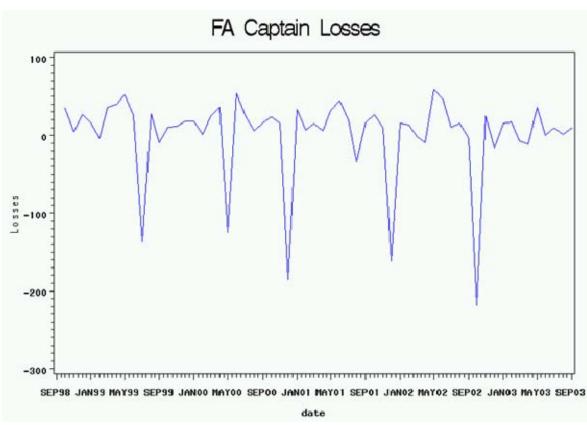


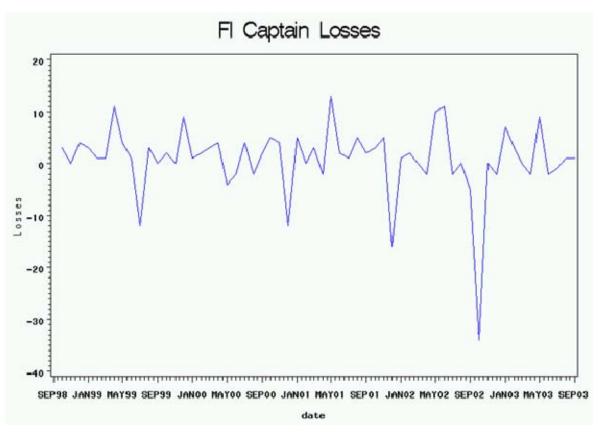


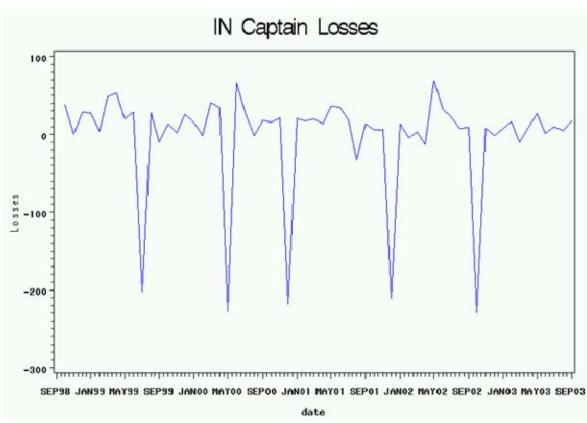


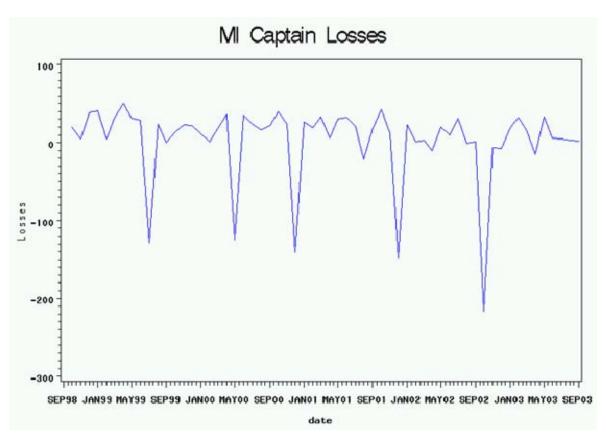


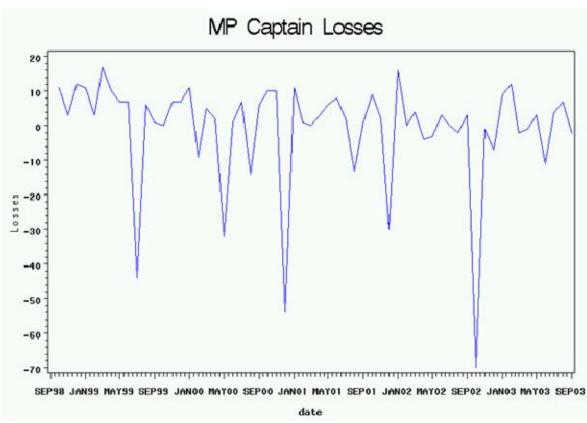


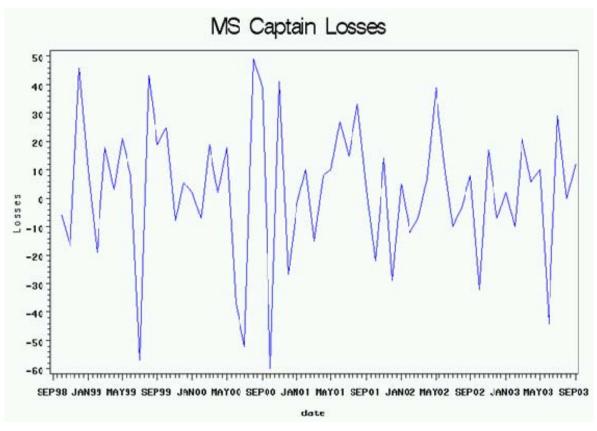


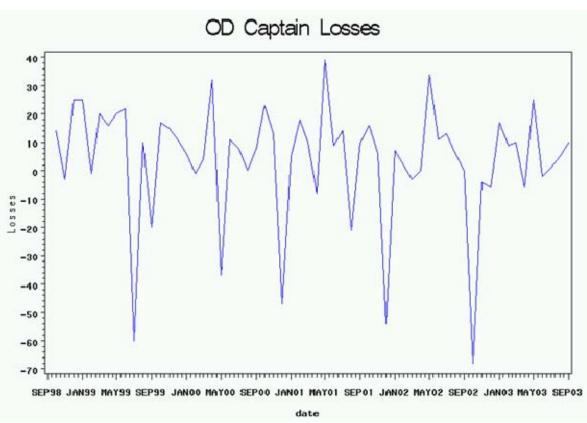


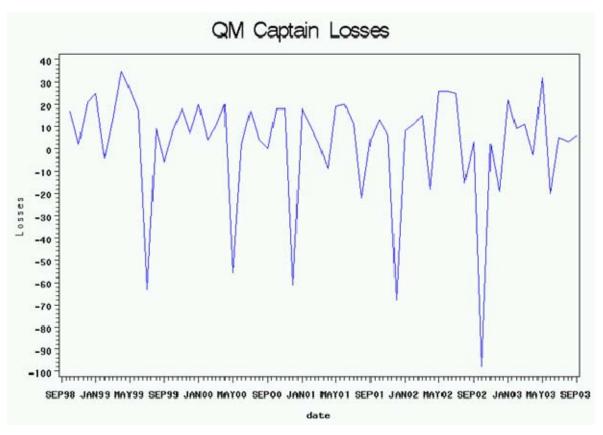


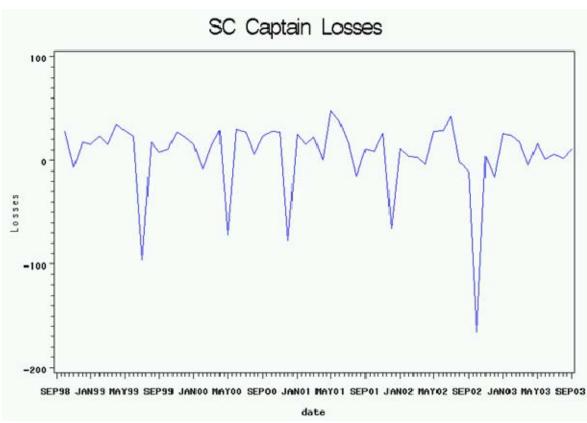


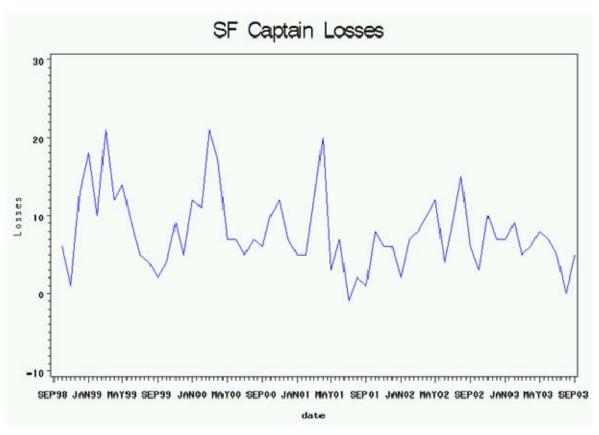


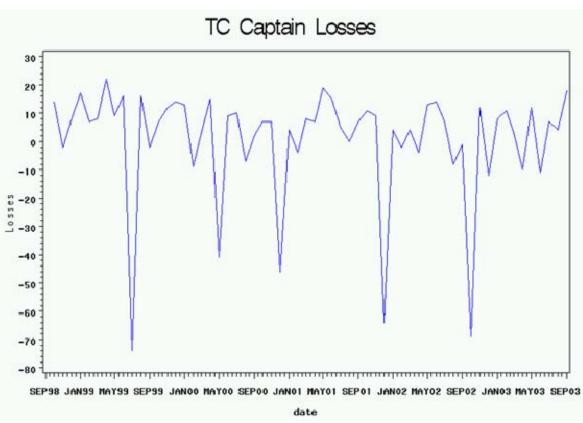




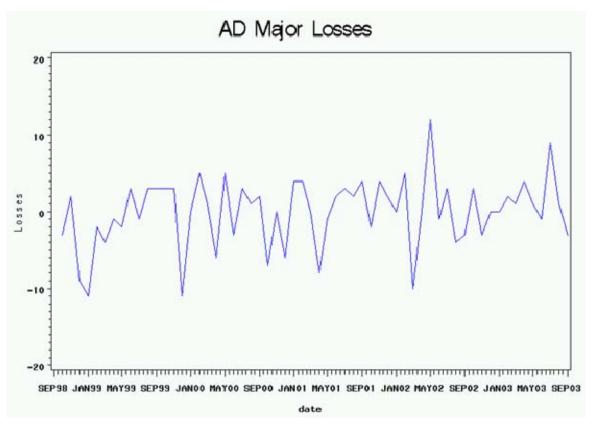


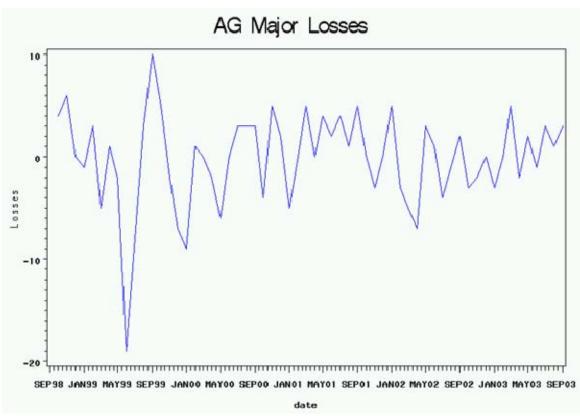


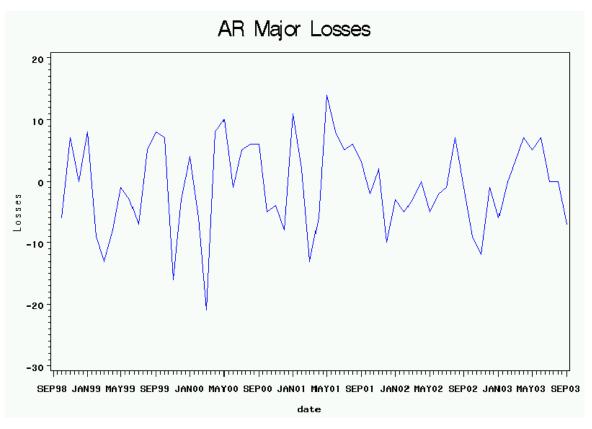


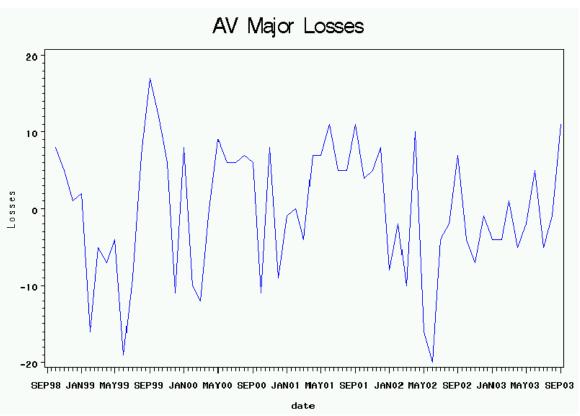


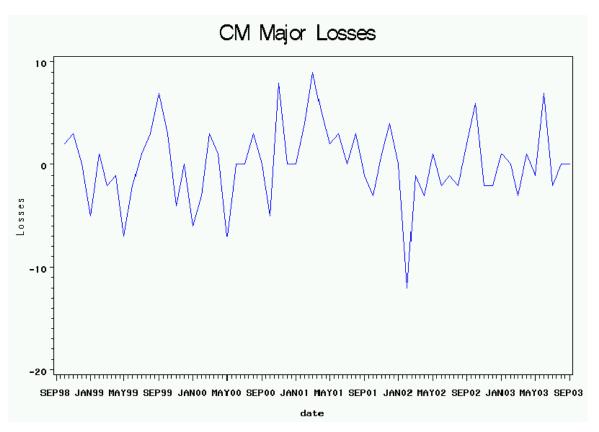
### B. MAJOR LOSS GRAPHS BY BRANCH

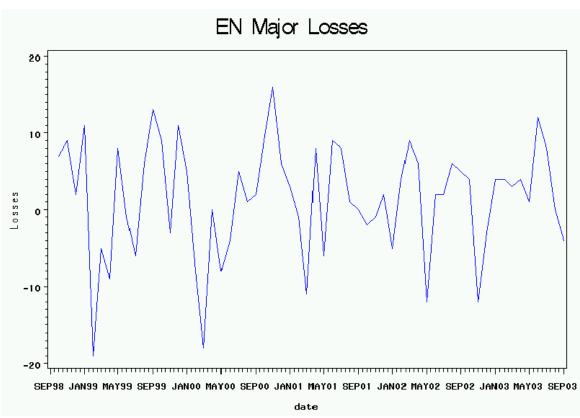


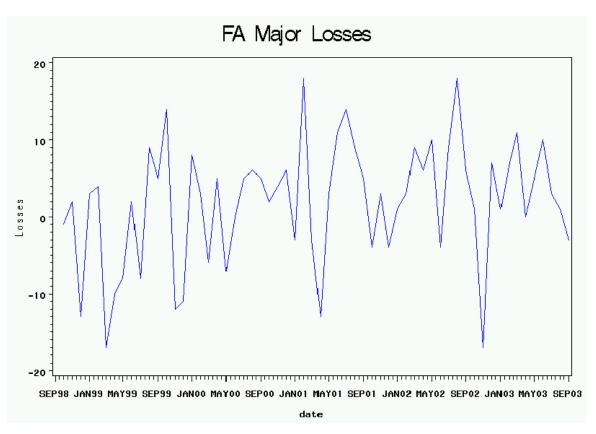


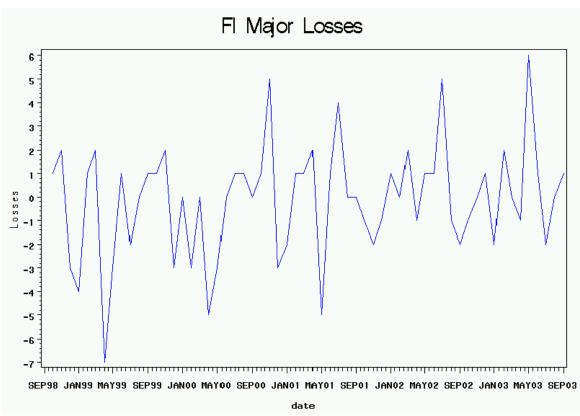


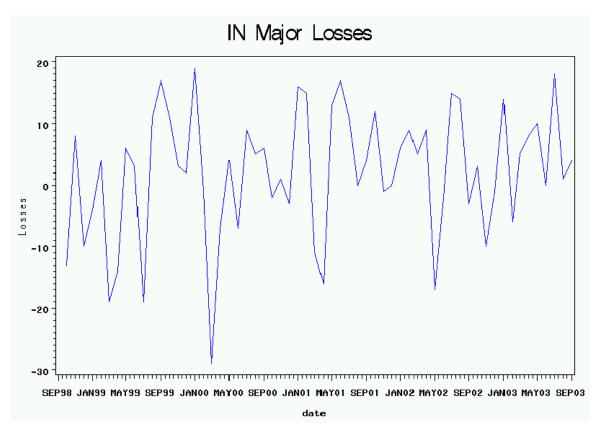


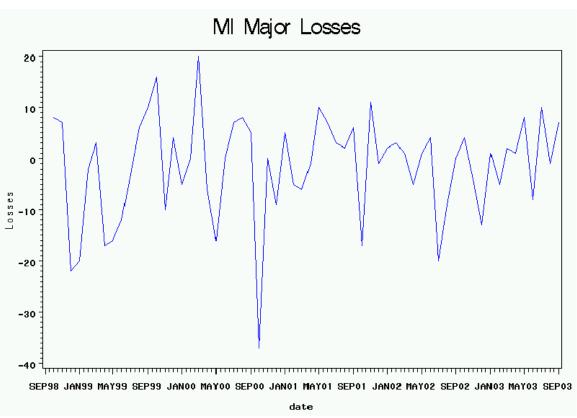


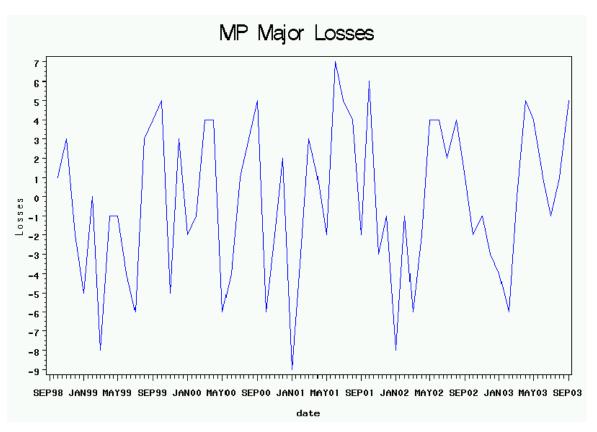


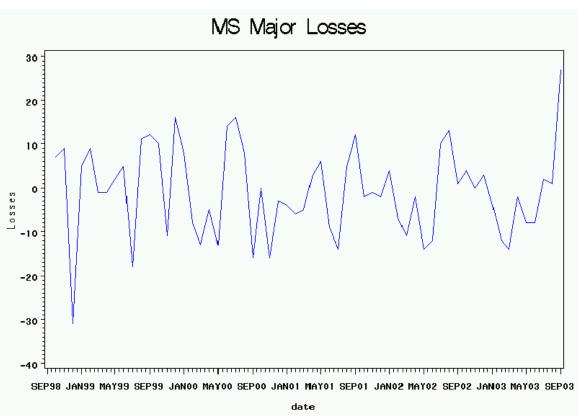


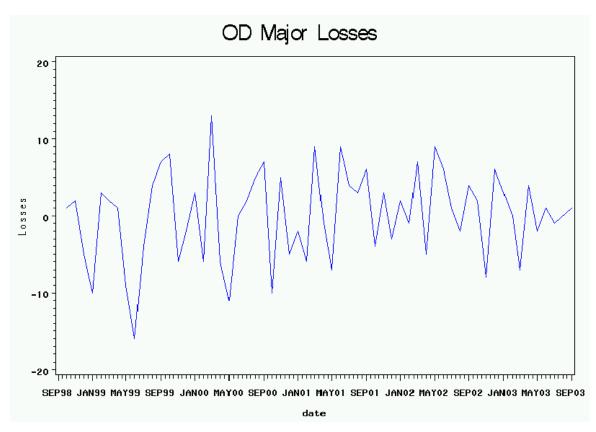


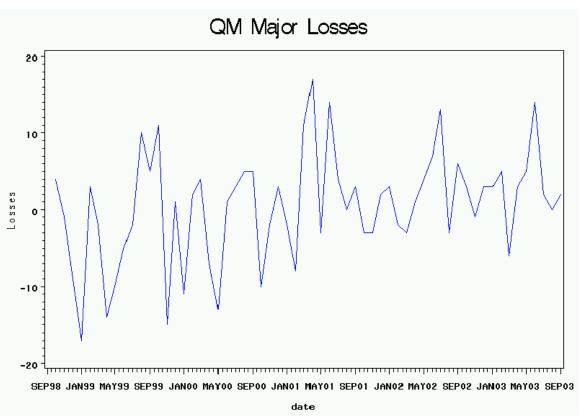


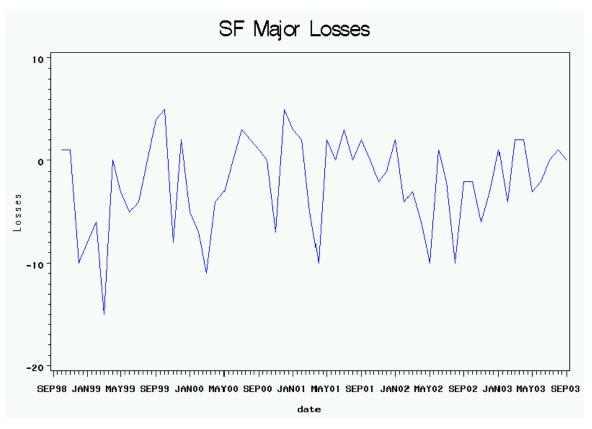


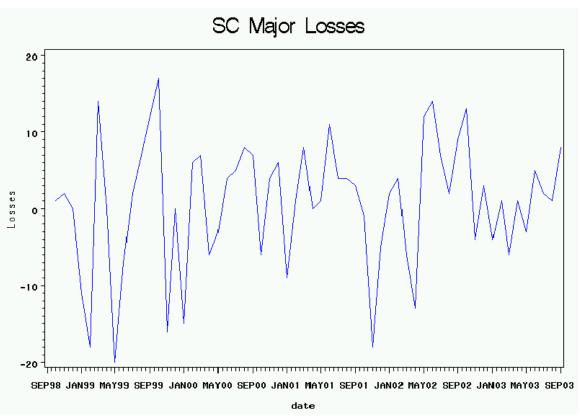


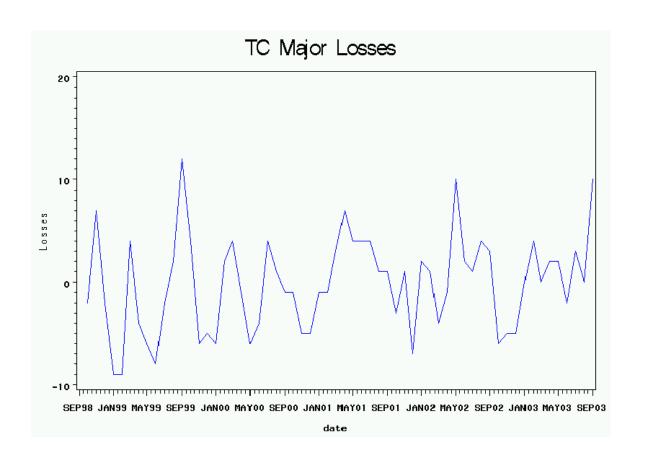












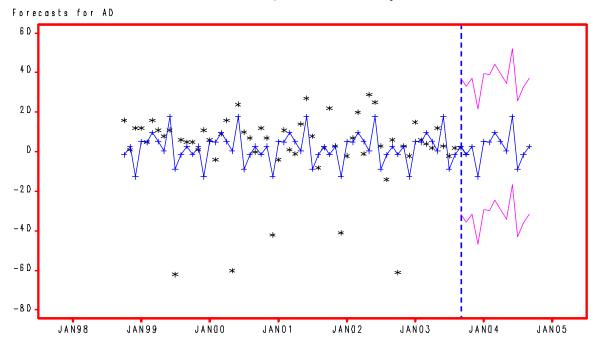
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# APPENDIX D FORECAST GRAPHS

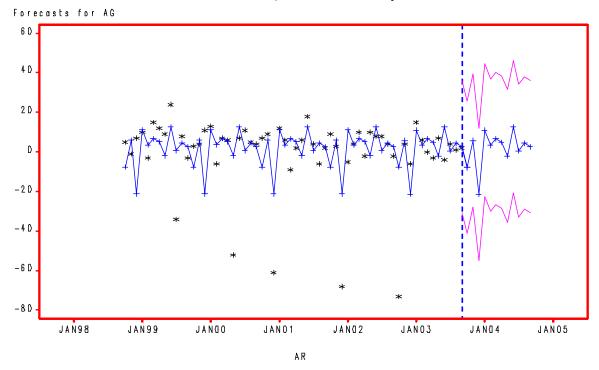
# A. CAPTAINS' FORECAST GRAPHS BY BRANCH

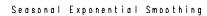
ΑD

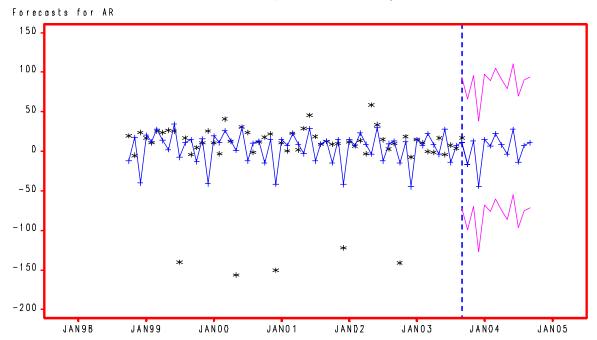
Seasonal Exponential Smoothing



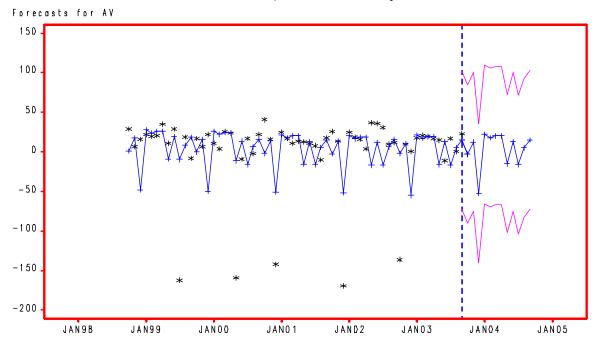
AG Seasonal Exponential Smoothing



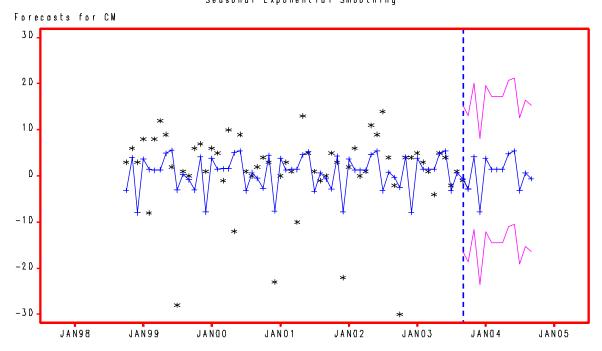




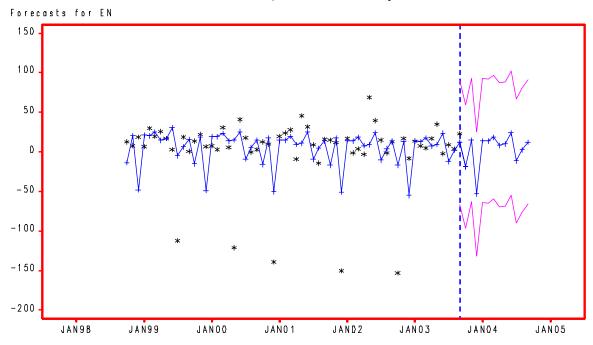
AV
Seasonal Exponential Smoothing



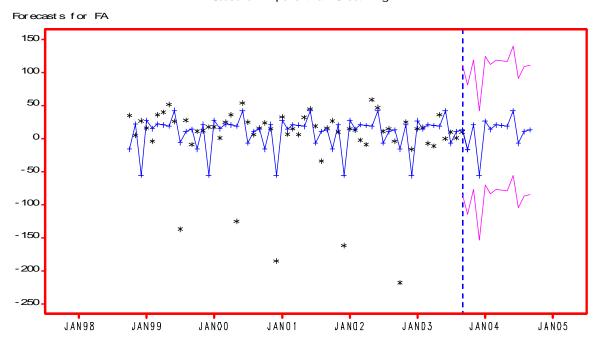
CM Seasonal Exponential Smoothing



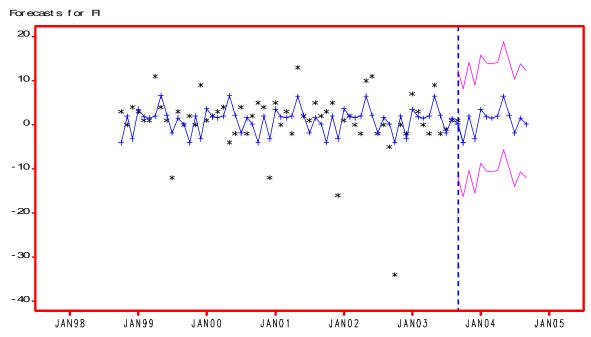
EN
Seasonal Exponential Smoothing



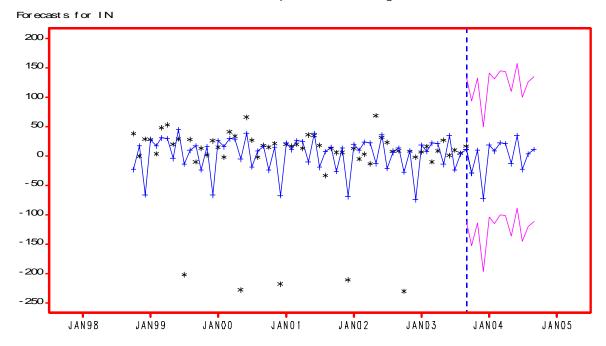
FA
Seasonal Exponential Shoothing



FI
Seasonal Exponential Shoothing

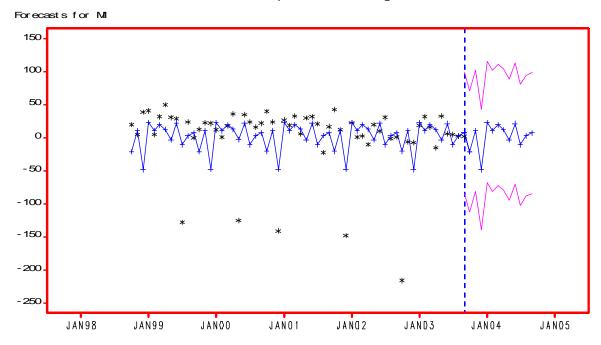


IN
Seasonal Exponential Shoothing

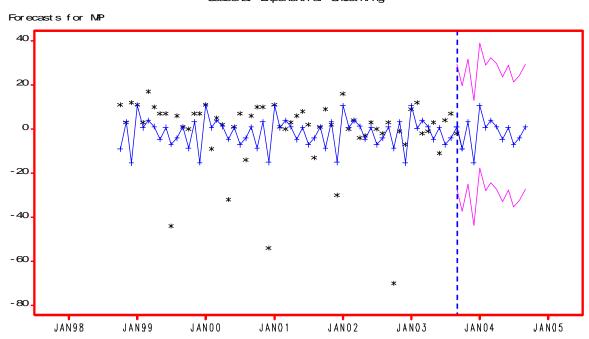


М

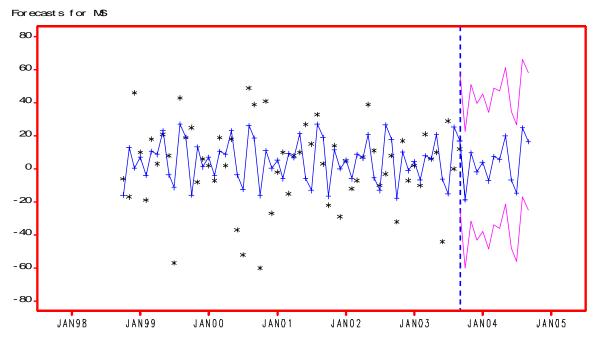
#### Seasonal Exponential Shoothing



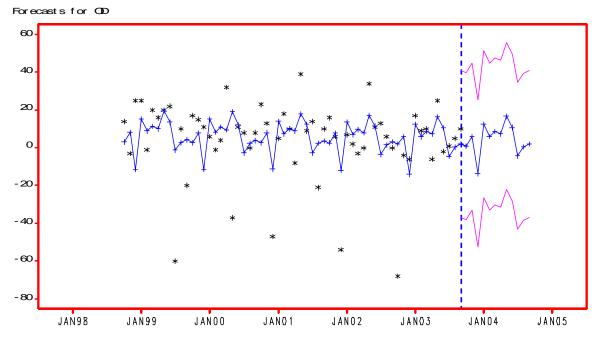
MP
Seasonal Exponential Shoothing



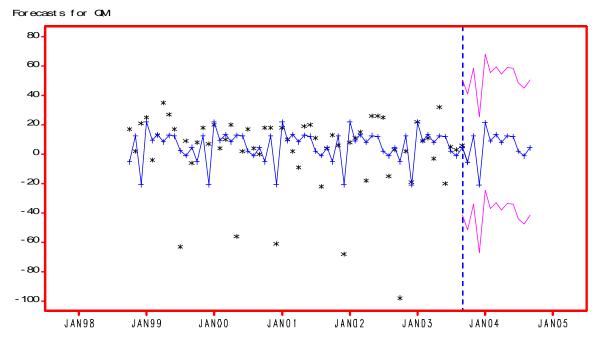
MS
Seasonal Exponential Shoothing



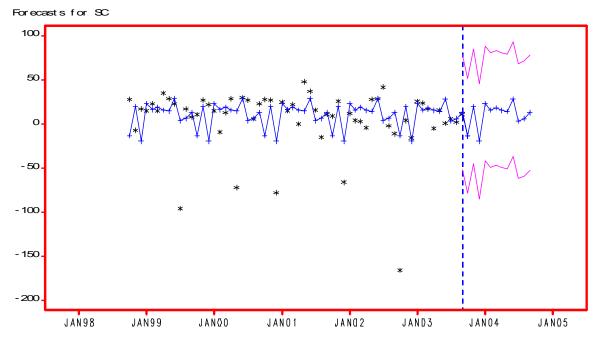




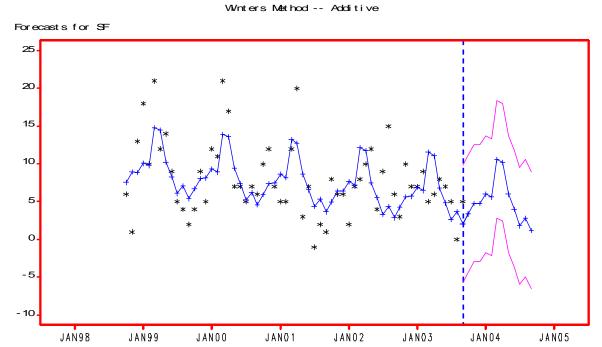
QM Seasonal Exponential Shoothing



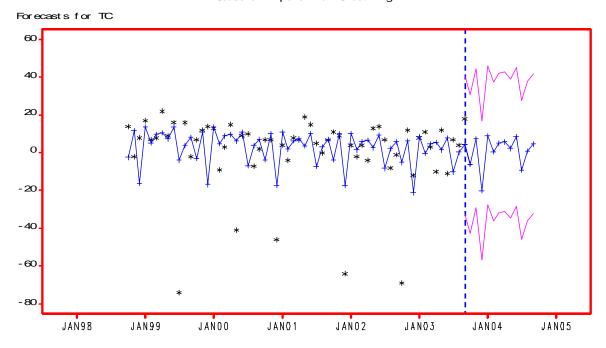
Sc Seasonal Exponential Shoothing



F



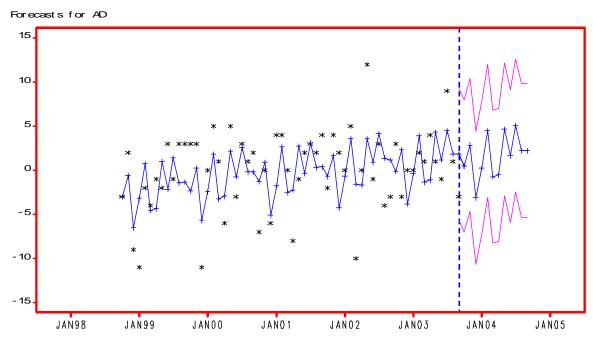
TC
Seasonal Exponential Shoothing



## B. MAJORS' FORECAST GRAPHS BY BRANCH

AD

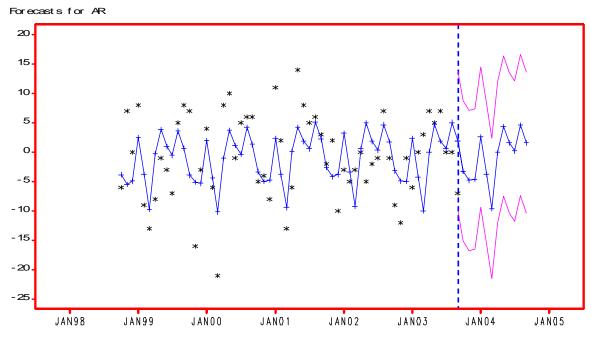
Winters Method -- Additive



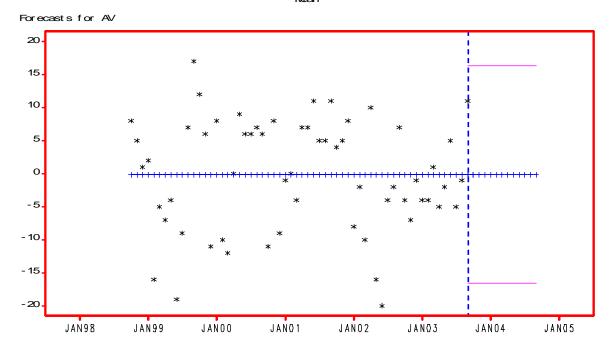
AG
Seasonal Exponential Shoothing

Forecasts for AG 15 10 5 0 -5 - 10 - 15 - 20 JAN98 JAN05 JAN99 JAN00 JAN01 JAN02 JAN03 JAN04

AR
Seasonal Exponential Shoothing

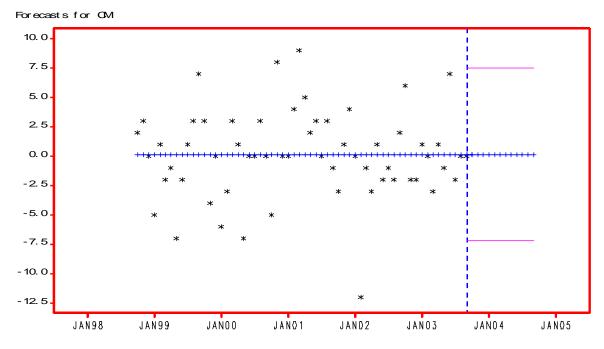


AV Man

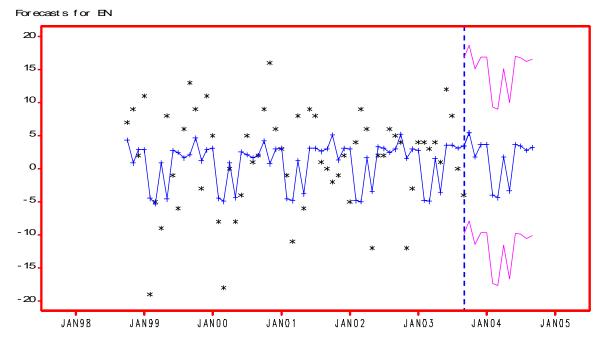


ФМ

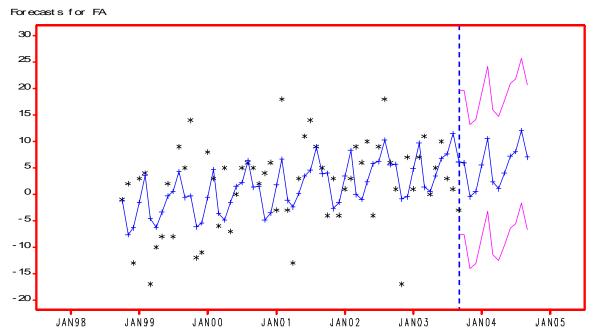
Mean



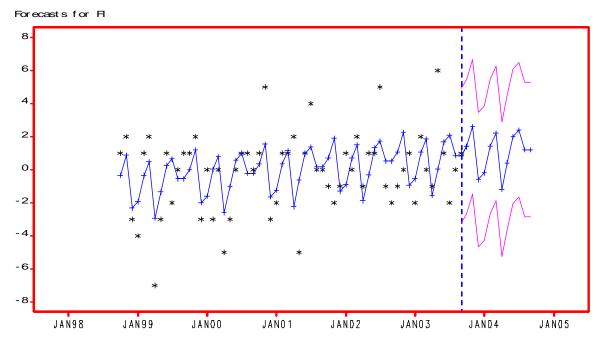
EN
Seasonal Exponential Shoothing



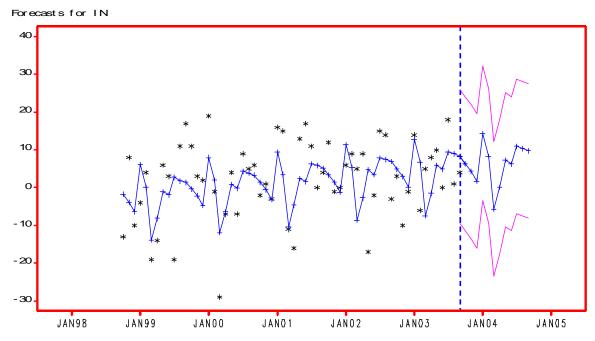
FA
Whaters Method -- Additive



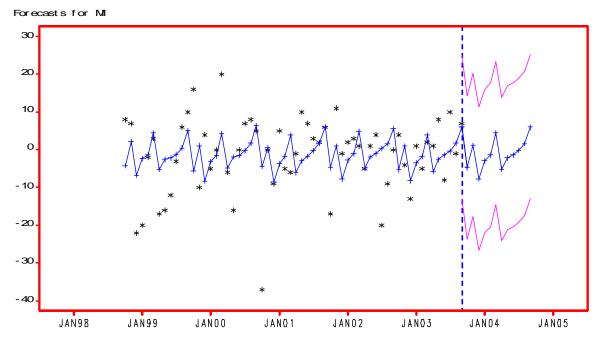
FI
Winters Method -- Additive



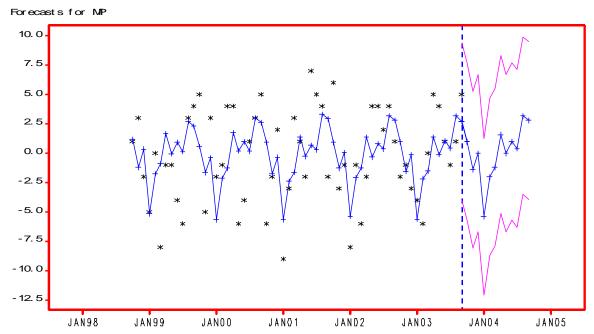
IN
Whaters Method -- Additive



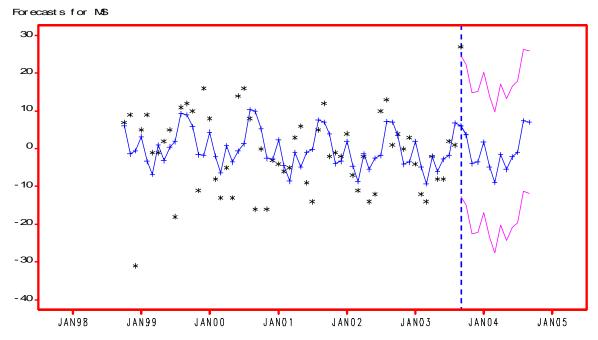
## MI Seasonal Exponential Shooothing



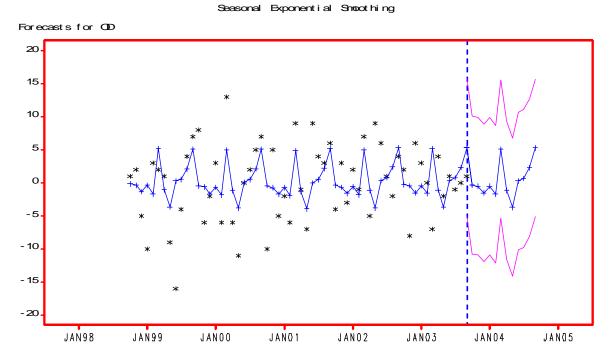
MP
Seasonal Exponential Shoothing



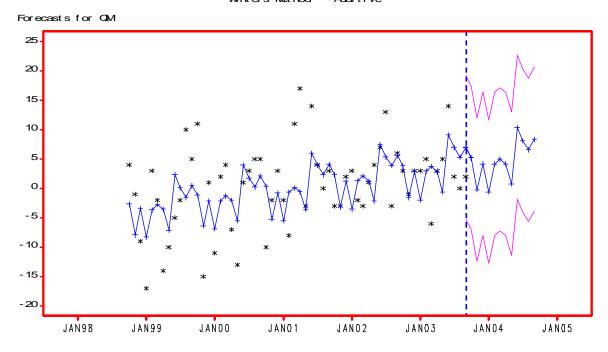
M6
Seasonal Exponential Shoothing



OD

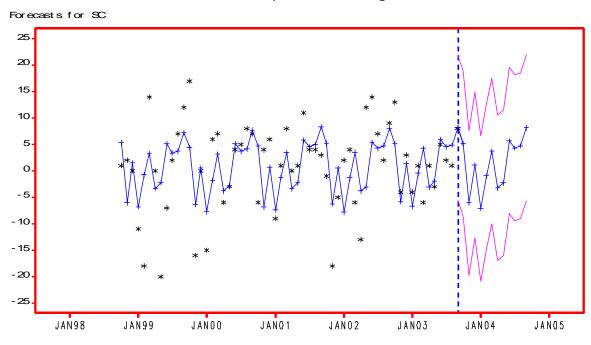


QM Winters Method -- Additive

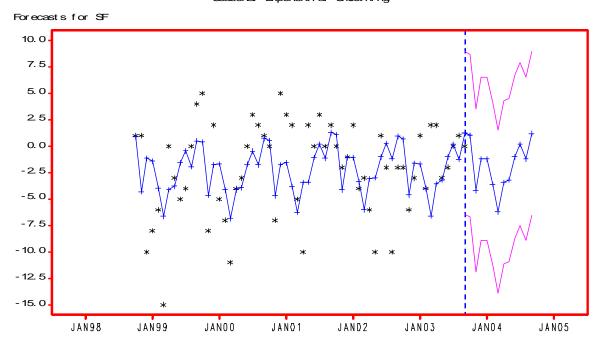


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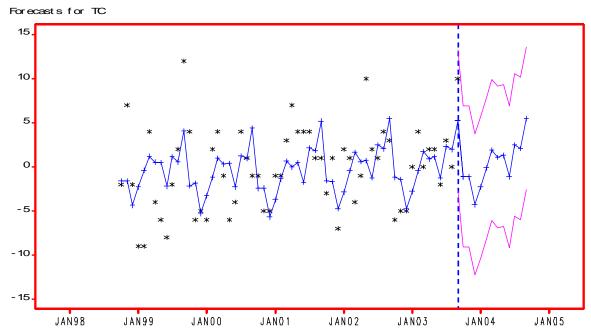
#### Seasonal Exponential Shoothing



SE
Seasonal Exponential Shoothing



TC
Seasonal Exponential Shoothing



#### APPENDIX E DICKEY-FULLER TEST

#### A. DICKEY-FULLER SAS CODE FOR MAJORS' DATA

```
OPTIONS PAGENO = 1 LINESIZE = 74 PAGESIZE = 64;
title 'Dickey Fuller Test for Stationary Series';
data Majors;
INFILE 'C:\Documents and Settings\CptMajData\MajNoNames.txt' DLM='09'X
DSD MISSOVER;
INPUT
ΑD
     AG
           AR
                 ΑV
                             ΕN
                                  FΑ
                                        ТŦ
                                              TN MT
                                                          MP
                                                                 MS
                       CM
     OD
           ΟM
                 SC
                       SF
                             TC;
date=intnx('month','010CT1998'd, n -1); /*creation of date variable*/
format date monyy5.;
PROC ARIMA DATA = MAJORS; identify var = AD
                                              STATIONARITY=(adf=(0));
/*adf=0, output is not a regression on the immediately previous
output*/
title 'AD Majors';
                    run;
PROC ARIMA DATA = MAJORS;
                           identify var = AG
                                               STATIONARITY=(adf=(0));
title 'AG Majors';
                   run;
PROC ARIMA DATA = MAJORS;
                           identify var = AR
                                               STATIONARITY=(adf=(0));
title 'AR Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = AV
                                               STATIONARITY=(adf=(0));
title 'AV Majors';
                   run;
PROC ARIMA DATA = MAJORS; identify var = CM
                                               STATIONARITY=(adf=(0));
title 'CM Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = EN
                                               STATIONARITY=(adf=(0));
title 'EN Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = FA
                                               STATIONARITY=(adf=(0));
title 'FA Majors';
PROC ARIMA DATA = MAJORS;
                           identify var = FI
                                               STATIONARITY=(adf=(0));
title 'FI Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = IN
                                               STATIONARITY=(adf=(0));
title 'IN Majors';
                   run;
PROC ARIMA DATA = MAJORS;
                           identify var = MI
                                               STATIONARITY=(adf=(0));
title 'MI Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = MP
                                               STATIONARITY=(adf=(0));
title 'MP Majors';
                    run;
PROC ARIMA DATA = MAJORS;
                           identify var = MS
                                               STATIONARITY=(adf=(0));
title 'MS Majors';
                    run;
PROC ARIMA DATA = MAJORS;
                           identify var = OD
                                               STATIONARITY=(adf=(0));
title 'OD Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = QM
                                               STATIONARITY=(adf=(0));
title 'QM Majors';
PROC ARIMA DATA = MAJORS;
                           identify var = SC
                                               STATIONARITY=(adf=(0));
title 'SC Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = SF
                                               STATIONARITY=(adf=(0));
title 'SF Majors'; run;
PROC ARIMA DATA = MAJORS;
                           identify var = TC
                                               STATIONARITY=(adf=(0));
title 'TC Majors';
run;
```

#### B. DICKEY-FULLER SAS CODE FOR CAPTAINS' DATA

```
OPTIONS PAGENO = 1 LINESIZE = 74 PAGESIZE = 64;
title 'Dickey Fuller Test for Stationary Series';
data Majors;
INFILE 'C:\Documents and Settings\CptMajData\CaptNoNames.txt' DLM='09'X
DSD MISSOVER;
INPUT
                                         FI
                                                IN
                                                      MΙ
                                                            MΡ
                                                                  MS
AD
      AG
            AR
                  ΑV
                        CM
                              EN
                                    FA
      OD
                  SC
                        SF
                              TC;
            QM
date=intnx('month','010CT1998'd,_n_-1); /*creation of date variable*/
format date monyy5.;
PROC ARIMA DATA = CAPTAINS; identify var = AD STATIONARITY=(adf=(0));
/*adf=0, output is not a regression on the immediately previous
output*/
title 'AD Majors';
                     run;
PROC ARIMA DATA = CAPTAINS;
                              identify var = AG STATIONARITY=(adf=(0));
title 'AG CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = AR STATIONARITY=(adf=(0));
title 'AR CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = AV STATIONARITY=(adf=(0));
title 'AV CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = CM STATIONARITY=(adf=(0));
title 'CM CAPTAINS';
                       run;
                              identify var = EN STATIONARITY=(adf=(0));
PROC ARIMA DATA = CAPTAINS;
title 'EN CAPTAINS';
                       run;
PROC ARIMA DATA = CAPTAINS;
                              identify var = FA STATIONARITY=(adf=(0));
title 'FA CAPTAINS';
                              identify var = FI STATIONARITY=(adf=(0));
PROC ARIMA DATA = CAPTAINS;
title 'FI CAPTAINS';
                       run;
PROC ARIMA DATA = CAPTAINS;
                              identify var = IN STATIONARITY=(adf=(0));
title 'IN CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = MI STATIONARITY=(adf=(0));
title 'MI CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = MP STATIONARITY=(adf=(0));
title 'MP CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = MS STATIONARITY=(adf=(0));
title 'MS CAPTAINS';
                       run;
PROC ARIMA DATA = CAPTAINS;
                              identify var = OD STATIONARITY=(adf=(0));
title 'OD CAPTAINS';
                       run;
PROC ARIMA DATA = CAPTAINS;
                             identify var = QM STATIONARITY=(adf=(0));
title 'QM CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = SC STATIONARITY=(adf=(0));
title 'SC CAPTAINS';
                       run:
PROC ARIMA DATA = CAPTAINS;
                              identify var = SF STATIONARITY=(adf=(0));
title 'SF CAPTAINS';
PROC ARIMA DATA = CAPTAINS;
                              identify var = TC STATIONARITY=(adf=(0));
title 'TC CAPTAINS';
run;
```

# APPENDIX F DICKEY FULLER UNIT ROOT TEST RESULTS

## A. TEST RESULTS FOR MAJORS BY BRANCH

<b>AD Majors</b> Dickey-Fuller Unit Root Tests										
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F			
Zero Mean Single Mean Trend	0 0 0		<. 0001 0. 0005 0. 0001	-7. 86 -7. 80 -8. 17	<. 0001 0. 0001 <. 0001	30. 39 33. 45	0. 0010 0. 0010			
		Di ckey	<b>AG Maj</b> -Fuller Un		ests					
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F			
Zero Mean Single Mean Trend	0 0 0	-43. 1895 -43. 2857 -43. 6260	<. 0001 0. 0005 0. 0001	-5. 80 -5. 77 -5. 78	<. 0001 0. 0001 <. 0001	16. 62 16. 75	0. 0010 0. 0010			
		Di ckey	<b>AR Maj</b> -Fuller Un		ests					
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F			
Zero Mean Single Mean Trend	0 0 0	-48. 1033 -48. 4617 -48. 5397	<. 0001 0. 0005 0. 0001	-6. 30 -6. 29 -6. 23	<. 0001 0. 0001 <. 0001	19. 78 19. 45	0. 0010 0. 0010			
		Di ckey	<b>AV Maj</b> -Fuller Un		ests					
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F			
Zero Mean Single Mean Trend	0 0 0	-44. 1655 -44. 2187 -44. 1601	<. 0001 0. 0005 0. 0001	-5. 85 -5. 80 -5. 72	<. 0001 0. 0001 <. 0001	16. 82 16. 53	0. 0010 0. 0010			
	<b>CM Majors</b> Dickey-Fuller Unit Root Tests									
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F			
Zero Mean Single Mean Trend	0 0 0	-51. 6871 -51. 7220 -51. 7853	<. 0001 0. 0005 0. 0001	-6. 74 -6. 68 -6. 64	<. 0001 0. 0001 <. 0001	22. 34 22. 02	0. 0010 0. 0010			
<b>EN Majors</b> Dickey-Fuller Unit Root Tests										
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F			
Zero Mean Single Mean Trend	0 0 0	-48. 9095 -50. 7496 -51. 0346	<. 0001 0. 0005 0. 0001	-6. 44 -6. 56 -6. 53	<. 0001 0. 0001 <. 0001	21. 53 21. 35	0. 0010 0. 0010			
<b>FA Majors</b> Dickey-Fuller Unit Root Tests										
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F			
Zero Mean Single Mean Trend	0 0 0	-49. 6803 -52. 5185 -57. 5397	<. 0001 0. 0005 0. 0001	-6. 49 -6. 75 -7. 22	<. 0001 0. 0001 <. 0001	22. 76 26. 06	0. 0010 0. 0010			

FI Majors Dickey-Fuller Unit Root Tests Type Lags Rho Pr < Rho Tau Pr < Tau F Pr > F<. 0001 Zero Mean 0 -58. 3079 <. 0001 -7.53 Single Mean 0 -58. 5436 0.0005 -7.49 0.0001 28.06 0.0010 <. 0001 Trend -61.6434 0.0001 -7.88 31.06 0.0010 IN Majors Dickey-Fuller Unit Root Tests F Pr > FType Lags Rho Pr < Rho Tau Pr < Tau Zero Mean -51. 2325 <. 0001 -6.75 <. 0001 0 -6. 99 -7. 18 0 0.0005 0.0001 Single Mean -53. 4338 24.47 0.0010 -55. 9308 25. 79 0. 0010 Trend 0.0001 <. 0001 MI Majors Dickey-Fuller Unit Root Tests Type Lags Rho Pr < Rho Tau Pr < Tau F Pr > F<. 0001 <. 0001 Zero Mean 0 -55.0414 -7.13 26. 21 0. 0010 26. 92 0. 0010 0 -56. 4459 -57. 2748 0.0005 -7. 24 -7. 33 0.0001 Single Mean <. 0001 Trend 0.0001 MP Majors Dickey-Fuller Unit Root Tests F Pr > FType Lags Rho Pr < Rho Tau Pr < Tau Zero Mean 0 -49. 1987 <. 0001 -6.36 <. 0001 19.94 0.0010 Single Mean 0 -49. 3875 0.0005 -6.31 0.0001 Trend 0 -50. 1303 0.0001 -6.38 <. 0001 20.40 0.0010 MS Majors Dickey-Fuller Unit Root Tests Type Lags Rho Pr < Rho Tau Pr < Tau F Pr > FZero Mean 0 -54. 2321 <. 0001 -6.64 <. 0001 Single Mean 0 -54. 9283 0.0005 0.0001 22.00 0.0010 -6.63 -55.0431 0.0001 -6.53 <. 0001 21.59 0.0010 Trend **OD Majors**Dickey-Fuller Unit Root Tests Type Rho Pr < Rho Tau Pr < Tau F Pr > FLags Zero Mean -63. 7188 <. 0001 -8. 25 <. 0001 0 Si ngl e Mean 0 0.0005 -8.18 0.0001 33.46 0.0010 -63. 7237 -65. 2723 -8.34 34. 77 0. 0010 Trend 0.0001 <. 0001 QM Majors Dickey-Fuller Unit Root Tests Rho Pr < Rho Tau Pr < Tau F Pr > FLags Type <. 0001 -49. 3962 -6.48 <. 0001 Zero Mean 0 -49. 5918 20.73 0.0010 Single Mean 0 0.0005 -6.44 0.0001 -56.8417 Trend 0 0.0001 -7.29<. 0001 26.58 0.0010 SC Majors Dickey-Fuller Unit Root Tests

**SF Majors**Dickey-Fuller Unit Root Tests

Rho Pr < Rho

<. 0001

0.0005

0.0001

Type

Trend

Zero Mean

Single Mean

Lags

0

-52. 5200

-52. 9214

-53. 9843

-6.77

-6.76

-6.85

Tau Pr < Tau

<. 0001

0.0001

<. 0001

F Pr > F

22.88 0.0010

23.50 0.0010

Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0		<. 0001 0. 0005 0. 0001	-5. 21 -6. 11 -6. 24	<. 0001 0. 0001 <. 0001	18. 67 19. 49	0. 0010 0. 0010		
<b>TC Majors</b> Dickey-Fuller Unit Root Tests									
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-40. 6423 -40. 6483 -42. 7562	<. 0001 0. 0005 0. 0001	-5. 29 -5. 23 -5. 46	<. 0001 0. 0001 0. 0002	13. 76 14. 98	0. 0010 0. 0010		
B. TES	T RE	SULTS F	OR CAP	TAINS B	Y BRAN	СН			
		Di ckey	<b>AD CAPT</b> -Fuller Un		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-62. 8965 -63. 6830 -63. 7384	<. 0001 0. 0005 0. 0001	-8. 18 -8. 21 -8. 14	<. 0001 0. 0001 <. 0001	33. 73 33. 16	0. 0010 0. 0010		
		Di ckey	AG CAPT -Fuller Un		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-64. 4952 -64. 5145 -65. 2800	<. 0001 0. 0005 0. 0001	-8. 37 -8. 30 -8. 32	<. 0001 0. 0001 <. 0001	34. 41 34. 62	0. 0010 0. 0010		
		Di ckey	<b>AR CAPT</b> -Fuller Un		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-65. 9915 -66. 0335 -66. 0516	<. 0001 0. 0005 0. 0001	-8. 58 -8. 51 -8. 44	<. 0001 0. 0001 <. 0001	36. 25 35. 62	0. 0010 0. 0010		
		Di ckey	<b>AV CAPT</b> -Fuller Un		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-64. 7479 -64. 7891 -64. 7861	<. 0001 0. 0005 0. 0001	-8. 41 -8. 34 -8. 27	<. 0001 0. 0001 <. 0001	34. 78 34. 22	0. 0010 0. 0010		
		Di ckey	<b>CM CAPT</b> -Fuller Un		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-59. 2050 -60. 1702 -60. 3608	<. 0001 0. 0005 0. 0001	-7. 65 -7. 70 -7. 66	<. 0001 0. 0001 <. 0001	29. 65 29. 32	0. 0010 0. 0010		
<b>EN CAPTAINS</b> Dickey-Fuller Unit Root Tests									
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-64. 7757 -64. 8702 -64. 8856	<. 0001 0. 0005 0. 0001 FA CAPT	-8. 39 -8. 33 -8. 26	<. 0001 0. 0001 <. 0001	34. 70 34. 09	0. 0010 0. 0010		
<b>FA CAPTAINS</b> Dickey-Fuller Unit Root Tests									
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-66. 5425 -66. 5696 -67. 1268	<. 0001 0. 0005 0. 0001	-8. 69 -8. 62 -8. 60	<. 0001 0. 0001 <. 0001	37. 12 37. 03	0. 0010 0. 0010		

### Dickey-Fuller Unit Root Tests

Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-56. 8913 -57. 7385 -58. 7553	<. 0001 0. 0005 0. 0001	-7. 36 -7. 40 -7. 45	<. 0001 0. 0001 <. 0001	27. 35 27. 74	0. 0010 0. 0010		
IN CAPTAINS Dickey-Fuller Unit Root Tests									
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0		<. 0001 0. 0005 0. 0001	-8. 77 -8. 72 -8. 66	<. 0001 0. 0001 <. 0001	38. 00 37. 49	0. 0010 0. 0010		
		Di ckey	<b>MI CAPT</b> -Fuller Uni		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-63. 3598 -63. 5857 -64. 6840	<. 0001 0. 0005 0. 0001	-8. 21 -8. 17 -8. 24	<. 0001 0. 0001 <. 0001	33. 37 33. 96	0. 0010 0. 0010		
		Di ckey	MP CAPTA -Fuller Uni		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-66. 6224 -66. 7740 -68. 0074	<. 0001 0. 0005 0. 0001	-8. 71 -8. 66 -8. 75	<. 0001 0. 0001 <. 0001	37. 51 38. 26	0. 0010 0. 0010		
		Di ckey	<b>MS CAPT</b> -Fuller Uni		ests				
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-74. 9076 -75. 9249 -76. 1520	<. 0001 0. 0005 0. 0001	-10. 02 -10. 14 -10. 09	<. 0001 0. 0001 <. 0001	51. 43 50. 94	0. 0010 0. 0010		
		Di ckey	<b>OD CAPT/</b> Fuller Uni-		ests				
Type	Lags								
Zero Mean	Lugs	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Single Mean Trend	0 0 0	Rho -63. 2772 -65. 3567 -66. 0157	Pr < Rho <. 0001 0. 0005 0. 0001	Tau -8. 20 -8. 42 -8. 42	Pr < Tau <. 0001 0. 0001 <. 0001	35. 47 35. 50	Pr > F 0.0010 0.0010		
Single Mean	0	-63. 2772 -65. 3567 -66. 0157	<. 0001 0. 0005	-8. 20 -8. 42 -8. 42	<. 0001 0. 0001 <. 0001	35. 47	0. 0010		
Single Mean	0	-63. 2772 -65. 3567 -66. 0157	<. 0001 0. 0005 0. 0001 <b>QM CAPT</b>	-8. 20 -8. 42 -8. 42 <b>AI NS</b> it Root T	<. 0001 0. 0001 <. 0001	35.47 35.50	0. 0010		
Single Mean Trend	0 0 0	-63. 2772 -65. 3567 -66. 0157	<.0001 0.0005 0.0001 <b>OM CAPT</b> -Fuller Uni	-8. 20 -8. 42 -8. 42 <b>AI NS</b> it Root T	<. 0001 0. 0001 <. 0001	35.47 35.50	0. 0010 0. 0010		
Single Mean Trend  Type  Zero Mean Single Mean	0 0 0 0 Lags	-63. 2772 -65. 3567 -66. 0157 Di ckey Rho -64. 0282 -64. 6287 -65. 7068	<.0001 0.0005 0.0001 • CAPTA - Fuller Uni Pr < Rho <.0001 0.0005	-8. 20 -8. 42 -8. 42 AI NS t Root T Tau -8. 32 -8. 33 -8. 39	<. 0001 0. 0001 <. 0001 Fests Pr < Tau <. 0001 0. 0001 <. 0001	35. 47 35. 50 F 34. 69	0.0010 0.0010 Pr > F 0.0010		
Single Mean Trend  Type  Zero Mean Single Mean	0 0 0 0 Lags	-63. 2772 -65. 3567 -66. 0157 Di ckey Rho -64. 0282 -64. 6287 -65. 7068	<.0001 0.0005 0.0001 OM CAPTA -Fuller Uni Pr < Rho <.0001 0.0005 0.0001 SC CAPTA	-8. 20 -8. 42 -8. 42 AI NS 1 t Root T Tau -8. 32 -8. 33 -8. 39 AI NS t Root T	<. 0001 0. 0001 <. 0001 Fests Pr < Tau <. 0001 0. 0001 <. 0001	35. 47 35. 50 F 34. 69 35. 19	0.0010 0.0010 Pr > F 0.0010		
Single Mean Trend  Type  Zero Mean Single Mean Trend	0 0 0 0 Lags	-63. 2772 -65. 3567 -66. 0157 Di ckey Rho -64. 0282 -64. 6287 -65. 7068	<.0001 0.0005 0.0001 OM CAPT/ Fuller Uni Pr < Rho <.0001 0.0005 0.0001 SC CAPT/ Fuller Uni	-8. 20 -8. 42 -8. 42 AI NS 1 t Root T Tau -8. 32 -8. 33 -8. 39 AI NS t Root T	<.0001 0.0001 <.0001 Fests Pr < Tau <.0001 0.0001 <.0001	35. 47 35. 50 F 34. 69 35. 19	0.0010 0.0010 Pr > F 0.0010 0.0010		
Single Mean Trend  Type  Zero Mean Single Mean Trend  Type  Zero Mean Single Mean	0 0 0 0 Lags 0 0	-63. 2772 -65. 3567 -66. 0157 Di ckey Rho -64. 0282 -64. 6287 -65. 7068 Di ckey Rho -59. 9510 -61. 4969 -62. 2802	<. 0001 0. 0005 0. 0001 Pr < Rho <. 0001 0. 0005 0. 0001 SC CAPTA Pr < Rho <. 0001 0. 0005	-8. 20 -8. 42 -8. 42 AI NS t Root T  Tau -8. 32 -8. 33 -8. 39 AI NS t Root T  Tau -7. 77 -7. 90 -7. 92 AI NS	<. 0001 0. 0001 <. 0001 Fests Pr < Tau <. 0001 <. 0001 Fests Pr < Tau <. 0001 0. 0001 0. 0001 0. 0001	35. 47 35. 50 F 34. 69 35. 19	0.0010 0.0010 Pr > F 0.0010 0.0010 Pr > F		
Single Mean Trend  Type  Zero Mean Single Mean Trend  Type  Zero Mean Single Mean	0 0 0 0 Lags 0 0	-63. 2772 -65. 3567 -66. 0157 Di ckey Rho -64. 0282 -64. 6287 -65. 7068 Di ckey Rho -59. 9510 -61. 4969 -62. 2802	<. 0001 0. 0005 0. 0001 Pr < Rho <. 0001 0. 0005 0. 0001 SC CAPT/ -Fuller Uni Pr < Rho <. 0001 0. 0005 0. 0001 SF CAPT/	-8. 20 -8. 42 -8. 42 -8. 42  AI NS 1	<. 0001 0. 0001 <. 0001 Fests Pr < Tau <. 0001 <. 0001 Fests Pr < Tau <. 0001 0. 0001 0. 0001 0. 0001	35. 47 35. 50 F 34. 69 35. 19 F 31. 22 31. 35	0.0010 0.0010 Pr > F 0.0010 0.0010 Pr > F		
Single Mean Trend  Type  Zero Mean Single Mean Trend  Type  Zero Mean Single Mean Trend	Lags 0 0 0 Lags 0 0 Lags 0 0 Lags	-63. 2772 -65. 3567 -66. 0157 Di ckey Rho -64. 0282 -64. 6287 -65. 7068 Di ckey Rho -59. 9510 -61. 4969 -62. 2802 Di ckey	<. 0001 0. 0005 0. 0001  OM CAPT/ -Fuller Uni Pr < Rho <. 0001 0. 0005 0. 0001  SC CAPT/ -Fuller Uni Pr < Rho <. 0001 0. 0005 0. 0001  SF CAPT/ -Fuller Uni	-8. 20 -8. 42 -8. 42 -8. 42  AI NS 1	<.0001 0.0001 <.0001 Fests  Pr < Tau <.0001 0.0001 <.0001 Fests  Pr < Tau <.0001 0.0001 <.0001	35. 47 35. 50 F 34. 69 35. 19 F 31. 22 31. 35	0.0010 0.0010 Pr > F 0.0010 0.0010 Pr > F 0.0010 Pr > F		

Trend	0	-41. 1765	0. 0001	-5. 52	0.0002	15. 28	0. 0010		
TC CAPTAINS Dickey-Fuller Unit Root Tests									
Туре	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F		
Zero Mean Single Mean Trend	0 0 0	-68. 6754 -68. 7384 -69. 3366	<. 0001 0. 0005 0. 0001	-8. 96 -8. 89 -8. 87	<. 0001 0. 0001 <. 0001	39. 56 39. 40	0. 0010 0. 0010		

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